AD-A258 447

AFIT/GCA/LSY/92S-4

DTIC
ELECTE
DEC 21 1992
S C D

THE APPLICATION OF FUNCTION POINTS TO PREDICT SOURCE LINES OF CODE FOR SOFTWARE DEVELOPMENT

THESIS

Garland S. Henderson, Captain, USAF

AFIT/GCA/LSY/92S-4

92-32229

Approved for public release; distribution unlimited

The contents of this document are technically accurate, no sensitive items, detrimental ideas, or deleterious information are contained therein. Furthermore, the views expressed in the document are those of the author and do not necessarily reflect the views of the School of Systems and Logistics, the Air University, the United States Air Force, or the Department of Defense.

DTIC QUALITY INSPECTED 5

Accession For
NTIS GRA&I
DTIC TAB
Unannounced
Justification
By
Distribution/
Availability Codes
Dist | Avail and/or Special
A-1

AFIT/GCA/LSY/92S-4

THE APPLICATION OF FUNCTION POINTS TO PREDICT SOURCE LINES OF CODE FOR SOFTWARE DEVELOPMENT

THESIS

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Logistics Management

Garland S. Henderson, B.S.
Captain, USAF

September 1992

Approved for public release; distribution unlimited

Preface

The purpose of this research was to examine the use of function point analysis in estimating source lines of code for projects in the earliest stages in development. Past experience at the Electronic Systems Division, Hanscom AFB, had demonstrated the need to be able to predict program cost and level of effort during the initial stages in a program's lifecycle. I hoped that my AFIT thesis would prove beneficial in addressing this issue. Additionally, I hoped that a thesis related to the software estimation arena would better prepare me for the future challenges I would face in the Air Force. It has.

During this grueling effort, I had a lot of support from a number of people. The one I'd like to thank most is my fiancee, Mary Mouritsen. Without her loving support and patience throughout the thesis process, the thesis would not have been possible. I'd also like to thank Linda Weston for praying me through another tough time, as she has for years. I owe a great deal of thanks to my thesis advisors, Mr. Dan Ferens and Major Wendell Simpson. Without their patience, advice, and encouragement, this would have been a far more difficult task. I would also like to thank my family for their continuing support. A special thanks goes to Captain Robert Gurner for his pearls of wisdom and ideas.

Finally, I would like to thank God for his love and guidance during the thesis experience. As He continues to bless me, I hope that I will continue to grow in Him as He molds me through experiences like the thesis.

Garland S. Henderson

Table of Contents

Page

Page

List of Figures

List of Tables

AFIT/GCA/LSY/92S-4

Abstract

This research investigated the results of using function point analysis-based estimates to predict source lines of code (SLOC) for software development projects. The majority of software cost and effort estimating parametric tools are categorized as SLOC-based, meaning SLOC is the primary input. Early in a program, an accurate estimate of SLOC is difficult to project.

Function points, another parametric software estimating tool, bases software cost and effort estimates on the functionality of a system. This functionality is described by documents available early in a program.

Using a modeling methodology, the research focuses on function point's ability to accurately estimate SLOC in the military and commercial environments. Although a significant relationship exists in both environments, none of the models provided a goodness of fit, predictive capability, and significance level to make them acceptable models, especially noted in the variability of the estimates of SLOC. The need to use models developed in similar environments was made clear.

The concept of function point to SLOC conversion tables was assessed and was justified. However, the conversion tables to be used should be based on similar programs developed in similar environments. Universally applicable function point to SLOC conversion tables were not supported by this research.

THE APPLICATION OF FUNCTION POINTS TO PREDICT SOURCE LINES OF CODE FOR SOFTWARE DEVELOPMENT

I. *Introduction*

Only by effectively quantifying and measuring a software project effort, in size or man-hours, can a manager successfully manage a program. More specifically, a project manager needs to be able to derive an adequate cost and schedule estimate before that manager can manage the overall project effectively (14:147). By measuring software project status in size and man-hours, managers may improve the quality and accuracy of their cost estimates.

A software manager needs to plan and control the software development process. Planning involves using estimates of the size, costs, and projected schedule to allocate the needed resources to a software project to ensure completion. Control involves comparing actual software schedules, size and cost data to estimated data to assess performance of the software development team. These two managerial functions go hand-in-hand. Measurement of project parameters may lead to productivity improvement once inefficiencies and productivity problem areas are discovered. The military needs to be able to successfully estimate, measure, and manage military software efforts as well. In 1988, the House Armed Services Committee cut all procurement funding for the OTH-B Radar because the software was behind schedule (55:142).

In order to justify, fund, and staff a software project, managers must understand and be able to predict cost. Software cost estimation techniques are also necessary to give managers the information to make cost-benefit analysis, breakeven analysis, or make-or-buy decisions.

Background

In 1980, the annual cost of software in the U.S. was about 2% of the Gross National Product, approximately $40 billion. Since 1980, the software rate of growth has surpassed the economy's rate of growth(7:17) With demand for software rising 12% annually and the average length of software development programs growing by 25%, project managers involved with software development must be able to plan and control software efforts (55:144).

In the 1990, the Department of Defense spent approximately $30 billion on software (18:7b). A study of U.S. Defense Department mission critical software costs predicted a 12 percent annual growth rate from $11.4 billion in 1985 to $36 billion in 1995 (9:1462). As the Department of Defense steadily grows more reliant on software systems, it needs to develop accurate and reliable software cost estimation tools.

A study by Boehm describes three problem areas associated with the inability to provide accurate software cost estimates (7:30). First, without a reasonably accurate cost estimate, a project manager has no firm basis from which to compare budgets and schedules; nor does the manager have the ability to make accurate reports to management, the customer, or sales personnel. Second, without an accurate software cost estimate, it is impossible to formulate a valid hardware-software tradeoff analysis for

managerial decision-making. Third, project managers need to understand how well the software effort is proceeding in order to manage the overall project effectively. Otherwise, funding could be misallocated, or projects could be cut if the software effort is not provided in a timely manner.

Software Estimation Methodology Background

Numerous methods are available to help managers estimate software costs. Among these are analogy, bottom-up, expert opinion, parametric models, and top-down methods (47:198). Parametric models are the methods most often used by the Department of Defense and industry (20:88-1). Parametric models estimate via the use of mathematical formulas derived from statistical relationships between parameters of interest, called cost drivers, and the dependent variable being estimated, such as project cost, size or duration. Typically, these models are automated using software programs. Benefits of parametric models include their repeatability and ability to preform sensitivity and domain analyses (47:197).

Most parametric models used to estimate effort may be categorized as either Source Line of Code (SLOC) based models or Function Point based models (20:88-5). "Most of the existing models use the size of the software product as an independent variable; this is usually expressed in the number of lines of source code [SLOC]" (28:38, 44:417). Function point counting, instead of using estimated SLOC as an input, counts the number of user functions, then adjusts them for processing complexity to estimate level of effort on a project (44:418).

SLOC is a measure of the size of a software project and is typically not considered a measure of software effort. When someone in the software

estimation profession speaks of effort, they are typically speaking of the number of man-months or cost associated with a project (18). However, the relationship between SLOC and level of effort is so pronounced that SLOC is actually used as a significant predictor in many established effort estimating models (8:17, 44:417, 2:639, 28:38). Early in the lifecycle of a software program, managers do not know SLOC ahead of time. However, managers do know function points which are based on the functionality of the system. This research investigates the ability of function points to predict SLOC so that managers can use the SLOC based models.

Although most software effort estimation models are SLOC based, some studies have found function point models to be superior to SLOC models for estimating effort in a software project (44:422, 2:643, 46:71). Kemerer evaluated four software cost estimation models. Kemerer found that the non-SLOC, function point based models performed better than the SLOC-based models. The data used in his study was from the business data-processing environment (44:427). In a similar study, Albrecht and Gaffney found that "basing applications development effort estimates on the amount of function to be provided by an application rather than an estimate of 'SLOC' may be superior" (2:644). Low and Jeffery concluded that function points are a more consistent a priori measure of system size than lines of code measures (46:64). It is not clear whether the weakness of the SLOC-based models used in these studies is due to "bad" models or inputs of inaccurate SLOC estimates. Inaccurate SLOC model inputs would definitely be a problem early in a program lifecycle before the first line of code is written.

While the above studies show that function points may yield better level of effort estimations, experts have also noted that there is a marked

relationship between function points and the lines of code in a project. One of the conclusions of the Kemerer study was that the "functionality represented by function points is related to eventual SLOC" (44:425). The Albrecht and Gaffney research concluded that the measures of effort and application size in SLOC are "strong functions" of function points (2:644). Genuchten and Koolen note that SLOC may be useful in describing completed projects, however, it is difficult to estimate SLOC for prediction of future projects (28:39). In other words, even though SLOC models are good predictors of effort, some method is needed to estimate SLOC early in program development.

The study by Albrecht and Gaffney found a "high degree of correlation between 'function points' and the eventual 'SLOC' (source lines of code) of the program. . . The strong degree of equivalency between 'function points and 'SLOC' shown in the paper suggests a two-step work-effort validation procedure, first using 'function points' to estimate 'SLOC,' and then 'SLOC' to estimate the work-effort" (2:639). As in the Albrecht and Gaffney study, applying function points to estimate SLOC in the pre-development stages of a project could prove useful if function points are a good measure of SLOC. The Albrecht and Gaffney study justifies this research.

The focus of this research is to determine the reliability and validity of function point based methodologies in providing SLOC estimations for Air Force and commercial projects. The concept will follow the concept presented in the Albrecht and Gaffney study (2). Function point based models may differ between the Air Force and industry due to differing developmental environments, techniques, and regulations. Jones explains that the amount of specifications, other supporting paperwork, and government requirements

could add significantly to the increase in the number of functions on military projects (35:18). If true, this would make military based function point counts higher than commercial function point counts on programs that perform the same basic functions.

Specific Problem

The purpose of this research is to test function point derived estimates on Air Force projects for reliability and validity in predicting SLOC values on completed Air Force software projects. Although estimates based on function points have been validated on non-Air Force projects (2, 35), their use has not been proven on Air Force projects. This may be due to the fact that many groups do not collect relevant software project data. According to Cuelenaere et al., there is a general lack of data providing relevant information on completed software projects (13:558). This lack of historical software costing and sizing data holds true for Air Force projects as well (17:37).

Objectives

The first objective of this research is to assess the strength of the predictive relationship of function point counts to source lines of code (SLOC) for the military given a detailed description of what the software is to functionally perform. By assessing the predictive capability of function points in estimating SLOC, function points ability to predict the level of effort required for development is implicitly tested. The second objective is to compare predictive capabilities of function points in the military and the commercial environment.

Research Question

How well do function point values predict SLOC for MIS/ADP projects?

Investigative Questions

Three specific questions must be answered in order to properly assess the usage of function point based methods in estimating SLOC:

1) How well do function point values predict SLOC for Air Force MIS/ADP projects?

2) Does the strength of the prediction relationship between function points and SLOC differ for Air Force and non-Air Force projects?

3) How well do function point-to-SLOC conversion tables created from Air Force and commercial data compare to function point-to-SLOC conversion tables provided by industry experts (61:164, 15:136, 34:73-78, 33:97-98)?

As a package, the answers to these investigative questions answer the research question, "how well do function point values predict SLOC for MIS/ADP projects?" If a strong relationship is discovered in the answer to question one, then function point counting could provide accurate SLOC estimates for future Air Force MIS/ADP programs. These SLOC estimates can then be used to predict effort using SLOC-based models. If the answer to question two is not affirmative, then function point counting might be used to provide accurate SLOC estimates for future commercial MIS/ADP programs. The conclusion whether function points are more effective at providing accurate SLOC estimates in the military or commercial environment is dependent on the answers to questions one and two. As Jones mentioned, military based function point counts could be higher than commercial function point counts on programs that perform the same basic

functions because of the additional constraints levied by regulation on military projects (35:18). Additionally, if both of the answers to questions one and two are affirmative, it will validate the other studies supporting the use of function points in estimating SLOC for MIS/ADP programs. The third research question attempts to validate the use of function point to SLOC conversion tables for Air Force and commercial project effort estimation as well as further support historical findings in this area.

Organization of Research

This first chapter has highlighted the problem, provided a brief introduction to the area of study, and proposed research objectives and a set of investigative questions. The second chapter will review the literature pertaining to software cost estimation, particularly function point information, in detail. The third chapter will provide a step-by-step detailed methodology for testing the above investigative questions. This methodology is to the level of detail that would allow for duplication of this research study. The fourth chapter presents the analysis and findings. The fifth chapter provides a summary and recommendations.

II. Literature Review

Introduction

This section describes prior research on the estimation of SLOC and level of effort required for software projects. First, a description comparing research on function point counting and line of code based estimation methods is presented. Then, the mechanics of function point usage is presented. Then, a number of empirical validations of the function point method are discussed. The next section introduces Feature Points, a modified version of function points. Because function points have not been validated for embedded and realtime software systems, the use of Feature Points is being pursued as a better estimator. Finally, another modification to the original function point estimation model, called Mark (Mk) II Function Points, is introduced as well.

SLOC Models

Although many factors potentially influence the level of effort on a software project, the number of source instructions, SLOC, is among the most important. Boehm has identified the following factors as being less important: personnel/team capability, product complexity, use of modern programming practices, software required reliability, requirements volatility, and language experience (9:1465).

The IIT Research Institute found that more than 25 software cost models existed in 1988 (32). Some experts cited in the study found 127 potential attributes in the various models that could influence software cost. Many of the prominent models are variations on the basic effort equation,

$$E = c*a^b$$

where E = effort in some selected units, and a is normally the size of the project in lines of code, and b and c are empirically derived constants (12:195-196). The study points out that, "if the factors of the model developer's environment that generated the historical statistics differ from those of another organization, the use of the model as a predictor for the second organization will be unreliable at best" (12:196). The study also agrees with Boehm that "one critical input parameter in nearly every software cost estimating methodology is the size of the system, given in LOC [Lines of Code]" (12:196). Genuchten and Koolen concur that "most of the existing models use the size of the software product as an independent variable; this is usually expressed in the number of lines of source code" (28:38).

Humphrey states, "Line-of-code (LOC) estimates typically count all source instructions and exclude comments and blanks... Perhaps the most important advantage of the LOC is that it directly relates to the product to be built" (31:90-91). Furthermore, "size measures are important in software engineering because the amount of effort required to do most tasks is directly related to the size of the program involved... the line of code (LOC) measure is probably most practical for measuring program size" (31:309). Reese and Tamulevicz agree:

> The most popular measure of software size is the number of lines of code. The estimation of the number of lines of code is important since most cost estimating tools base their projected estimate upon this number. There are many other parameters used in conjunction with various cost estimating tools including complexity, personnel capabilities, and reliability requirements of the system to name a few.

However, the number of lines of source code is the most important factor. A poor lines of code estimate can result in a bad estimate of the total project effort (60:35).

Table 1, from a recent *Fortune* article on software programming, compares four different software projects as for their lines of code, labor required, and cost. It is readily apparent that the lines of code, labor required, and costs are all positively related to each other.

Table 1

Software Cost and Effort Comparisons

Project	Lines-of-Code	Labor (man-years)	Cost ($ millions)
1989 Lincoln Continental	83517	35	1.8
Lotus 1-2-3 v.3	400000	263	7
Citibank AutoTeller	780000	150	13.2
Space Shuttle	25600000	22096	1200

(64:100-108)

To summarize the above information, SLOC is a well-established, good estimator of effort.

Weaknesses of SLOC-based Estimating Models

For a number of years, software managers based their cost and schedule models on SLOC. Boehm identifies the biggest difficulty with using such models is that they require an estimate of SLOC to be developed, and

SLOC is extremely difficult to determine in advance (8:17). Ferens adds that one of the major problems in using SLOC for cost estimating is that this number is unknown until the program is written (19:1). Kemerer states, "SLOC was selected early as a metric by researchers, no doubt due to its quantifiability and seeming objectivity. Since then an entire subarea of research has developed to determine the best method of counting SLOC" (44:417). Kemerer goes on to say that many estimators complained about the "difficulties in estimating SLOC before a project was well under way."

To combat the problem of unknown SLOC, Albrecht and Gaffney suggest the use of a two-step software effort estimation procedure. They used function points to estimate SLOC, and then SLOC to estimate the work-effort. Albrecht and Gaffney had found a "high degree of correlation" between function points, SLOC, and the amount of effort to develop the code. Because of the "strong degree of equivalency" between function points and SLOC, they suggest a two-step level of effort validation procedure. The Albrecht and Gaffney study concluded that "it appears that basing applications development effort estimates on the amount of function to be provided by an application rather than an estimate of 'SLOC' may be superior" (2:644).

Jones observed a difficulty with the SLOC approach due to the fact that different languages require different numbers of statements required to implement one function point (33:97). However, Jones advances the concept that source statement per function point conversion tables could be developed for each programming language, similar to a chemistry periodic table of elements (34:73-78, 33:97-98). This would imply a direct linear relationship between function points and SLOC with a y-intercept of zero.

This concept was supported by two other authors. Dreger in his book, concurs with Jones (14:136). Reifer provides a SLOC per function point conversion table for 13 different languages. For example, the chart reflects that there are 100 COBOL SLOC per function point with a 0.913 correlation from his database (61:164). Industry experts don't agree on the exact conversion factors. For example, Jones differs from Reifer because Jones feels that there are 105 SLOC per function point (33:98, 34:76).

Without adjustment for language, SLOC is a poor metric for level of effort. The natural assumption with software metrics is that as improvements in productivity occur, they will be reflected in the metric. It was discovered that productivity measures expressed in SLOC paradoxically decreased as real productivity improved (65:21). By using a higher-order language, programmers are able to produce more with fewer lines of code. Thus, SLOC measures were showing programmer's productivity decreasing when their productivity was actually increasing. Higher order languages generally require less SLOC to perform the same functionality. When more powerful programming languages are used, the trend is to reduce the number of SLOC that must be produced for a given program or system (15:3).

Explanation of Function Point Concepts

To overcome problems with SLOC-based estimation, Albrecht developed a software effort evaluation method known as Function Point Analysis in 1979 (34:9). Function Point Analysis is dependent on the end-user defined functionality of the system. "Function Points measure software by quantifying the functionality external to itself, based primarily on logical

design" (27:3). With respect to 'quantifying the functionality,' the objectives of function point counting are to:

- Measure what the user requested and received
- Measure effort independent of technology used for implementation
- Provide a sizing metric to support quality and productivity analysis
- Provide a vehicle for software estimation
- Provide a normalization factor for software comparison (27:3).

The function point counting process needs to be simple to minimize overhead and be concise to ensure consistency (27:3). Function Point Analysis is based on the user's requirements. Dreger states, "A function point is defined as one end-user business function" (15:5). Function points are identified and categorized in a systematic manner.

Figure 1 depicts how the five function point categories are observed in a system working within and between *files, applications, and end* users. All of these are depicted above and can be categorized into one of the five categories listed below. The five categories of function points are:

- An *Internal Logical File (ILF)* is a user identifiable group of logically related data or control information maintained and utilized within the boundary of the application. An example would be the usage of memory files within an application or file.

- An *External Interface File (EIF)* is a user identifiable group of logically related data or control information utilized by the application which is maintained by another application. An example of this is depicted by information passing between A files and B files or between application A and application B such as a shared database.

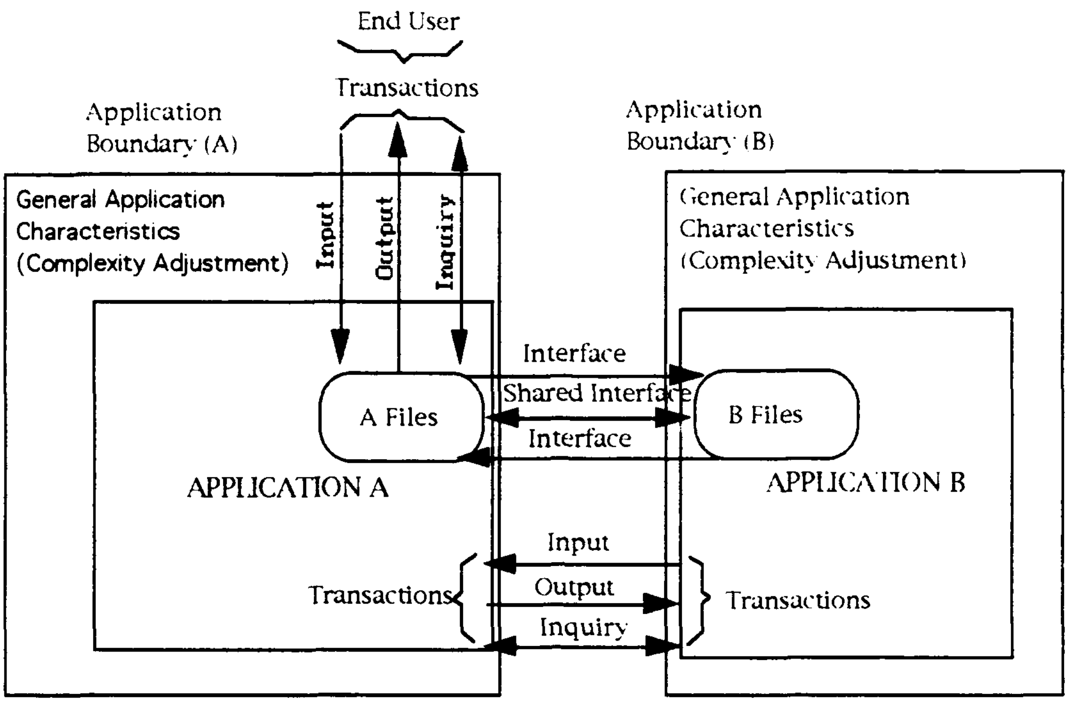


Figure 1. Relationships of Users, Applications, and Business Functions

(15:8)

• An *External Input (EI)* processes data or control information which enters the application's external boundary, and through a unique logical process, maintains an internal logical file, initiates or controls processing. An example of this would be the the arrowed lines leading from outside application A into it.

• An *External Output (EO)* processes data or control information which exits the application's external boundary. An example of this would be the the arrowed lines leading from inside application A out of it.

• An *External Inquiry (EQ)* is a unique input/output combination where an input causes an immediate retrieval of data and an internal logical file is not updated. An example of this would be the two-way arrows leading into and out of application A (59:4-8).

After categorizes and enumerating the function point component values, the ILF's, EIF's, EI's, EO's, and EQ's, the function point multiplies each

component by its functional complexity weighting factor. Each function point type is assigned its own weighting factor (low, average, or high) based on the number of record element types, data element types, and file types referenced for the function point type in question. This complexity adjustment was part of Albrecht's 1984 revision to function points:

> The impact of complexity was broadened so that the range became approximately 250 percent. To reduce the subjectivity of dealing with complexity, the factors that caused complexity to be higher or lower than normal were specifically enumerated and guidelines for their interpretation were issued. Instead of merely counting the number of inputs, outputs, master files, and inquiries as in the 1979 function point methodology, the current methodology requires that complexity be ranked as low, average, or high. In addition, a new parameter, interface files, has been added. . . . With the 1984 IBM implementation, each major feature such as external inputs must be evaluated separately for complexity (34:60).

Application of the functional complexity factor is based on the number of record element types, data element types, and file types referenced (25:5, 57:5-9). The sum of all the weighted component values produces the unadjusted function point value (15:7). The various weightings for each function type used to derive this unadjusted function point total is seen in Figure 2. For example, Albrecht's unadjusted function point model equation would be based on the following equation if each of the function point components were considered to have an average complexity:

$$UFP = 4EI + 5EO + 4EQ + 10ILF + 7EIF$$

Then, the unadjusted function point value, UFP above, is adjusted by applying a Value Adjustment Factor (VAF) (25:5). The VAF is based on 14 general system characteristics. Each characteristic is assigned a value

	Functional Complexity		
Function Type	Low	Average	High
External Inputs	x3	x4	x6
External Outputs	x4	x5	x7
Internal Logical Files	x7	x10	x15
External Interface	x5	x7	x10
External Inquiries	x3	x4	x6

Figure 2. Unadjusted Function Point Count Weighting Framework

(34:61)

between 0 and 5. The VAF is another complexity adjustment to the unadjusted function point total (34:67). The 14 VAF factors are listed below (25:6-7, 34:67-68, 57:9-12):

- data communications
- distributed data processing
- performance
- heavily used configuration
- transaction rate
- on-line data entry
- end user efficiency
- on-line update
- complex processing
- reusability
- installation ease
- operational ease
- multiple sites
- facilitate change

"In considering the weights of the 14 influential factors, the general guidelines are these: score a 0 if the factor has no impact at all on the application; score a 5 if the factor has a strong and pervasive impact; score a 2, 3, 4, or some intervening decimal value such as 2.5 if the impact is something in between" (34:65). For example, the data communication influential factor would be scored as follows (34:65):

0 - Batch applications
1 - Remote printing or data entry
2 - Remote printing and data entry
3 - A teleprocessing front end to the application
4 - Applications with significant teleprocessing
5 - Applications that are dominantly teleprocessing

These influential factors are then summed, and entered into the following equation:

$$VAF = sum * 0.01 + 0.65$$

The value adjustment factor has a range of 0.65 to 1.35. Adjusted function points are then calculated by multiplying VAF by the UFP total. For the remainder of this paper, the term "function point" will refer to the adjusted function point count.

Function Points' usefulness in size estimation spans a number of languages. In fact, it has been applied to over 250 different software languages (15:4). More recent information states that function points can be used to size more than 300 languages. The following are some examples from Capers Jones:

- COBOL requires an average of about 105 SLOC per function point.
- The Ada language requires about 71 SLOC per function point.

• The C language requires about 128 SLOC per function point (35:2).

By being dependent on end-user defined functionality, the assigned Function Point value will more closely match an application's requirement definition than will a lines of code methodology. Function point analysis "accurately and reliably evaluates (to within 10% for existing systems and 15-20% for planned systems):

- the business value of a system to the user
- project size, cost, and development time
- MIS shop programmer productivity and quality
- maintenance, modification, and customization effort
- feasibility of in-house development" (15:4)

Kemerer found that function point estimation models outperformed SLOC-based methods. For this study, Kemerer used data from 15 completed software projects relating to comprehensive business applications. He estimated man-months required with four uncalibrated models. (A model is considered calibrated when adjustment factors are updated based on historical data.) Two of the models used function point analysis; and two used lines of code methodology to arrive at estimates. Estimated number of man months for the two Lines of Code methods, COCOMO and SLIM, each over estimated the actual values by 601% and 772%, respectively. The two models using a function point methodology, FPA and ESTIMACS, each overestimated the actual values by 100% and 85%, respectively (13:559, 44:422). Ourada concludes that the software line of code estimation models used in his research were ineffective without calibration (58:5.1). One could conclude that an uncalibrated function point estimate may not be significantly accurate, however it will provide a much closer relative

estimate than Line of Code methods. To not calibrate a model prior to testing it would not make sense unless the the person either did not have the data from the historical projects or didn't have the time or knowledge to model properly.

Albrecht and Gaffney showed a relationship between function points and SLOC. The study used data from three organizations to calibrate four different SLOC estimation models based on function points. Testing these models at 17 other organizations showed a better-than-92% correlation between the estimated and actual number of lines of code (2:643). Low and Jeffery found that function points are a more consistent a priori measurement of system size than SLOC methods (46:71). Other studies further support the function point concept by showing that a similar number of functions are used to solve a given problem even where programming techniques differ (11:44). Apparently, function points perform well enough to be considered for usage in the workplace. As a case in point, the Air Force Standards Systems Center has transitioned to the use of function point counting methods for software estimation as an adjunct to lines of code methods (39).

Function Point Advantages and Disadvantages

When sizing a software effort for cost or measurement purposes, function point analysis sizes an application from an end-user rather than a programmer perspective. "There was found to be a strong correlation between program size in SLOC, and function points. In fact, the researchers concluded that function points could be more effective than size [SLOC] as a key parameter for estimating program cost, or level of output" (17:31).

Function points are well-validated for management information systems (17:34). Low and Jeffery found that estimating software effort with function points is recommended because function points measure the functionality delivered to the user. "In comparison, it is extremely difficult to estimate lines of code prior to the program specification stage" (46:69). One author feels that another advantage to function points is that it is "not excessively time consuming. . . [it is] reported that one corporation found that it takes between one and four hours for an analyst to count function points for a one-person-year project" (29:24).

The use of Function Points provides information on completeness, granularity, and usefulness of the software project by basing its output on such factors that impact the project as worker skills, methods, tools, languages, constraints, problems, and the office work environment. Once a reasonable sample of software projects have been measured and stored by a company, this measured data can be used to create customized estimating templates for other projects. "Such templates could be tailored exactly to match the tools, methods, [and] environment" of each company (35:6). It has been inferred that software managers must be able to size a software effort before it is possible to estimate the work involved. In the past, many such sizing estimates were based on expert opinion, similar project estimates, and historical information. Function points considers all of these in its estimate.

Function point analysis is flexible. "Ratios established for programming subactivities such as design, coding, integration, or testing often move in unexpected directions in response to unanticipated factors" (15:3). For example, the use of CASE tools will decrease coding and integration time but will require more upfront system design time. Also,

user requirements typically change in projects as they progress. Function points can be calibrated to take such contingencies into account. Because of the embedded expertise in function point software and user orientation, function point estimating tools "can augment and improve the capabilities of new managers or experienced managers facing new kinds of projects with which they have not dealt before" (35:4).

Despite the advantages to using function point based estimating methodologies, there are some disadvantages. Software estimating tools are expensive. A single tool may cost more than $15,000 due to the high market value of the expertise used to create the estimation tool (35:4). "A weakness of function point models is that they are generally not regarded as suitable for applications other than data processing, such as for real time programs" (17:32). Since defining function points involves learning a new "language", it can be comparatively hard to learn and time-consuming. Function point related methods will require more upfront, start-up work (65:20).

Feature Points

In 1986, Feature Points, an extended version of function points, was developed for systems with embedded and real-time software. Because it has been found that function points are not suitable for applications other than data processing, the basic function point equation has been modified with additional inputs to adapt it to scientific and real-time applications. Feature Points, an experimental approach, includes the same five parameters as function points and one additional parameter accounting for the number of algorithms included in the application. Systems and embedded software applications tend to be high in algorithmic processing (36:4). Once again,

"an algorithm is defined as the set of rules which must be completely expressed in order to solve a significant computational problem" (65:30). Since algorithms in a program account for a significant portion of real-time, embedded, and scientific programs, function points do not accurately predict their size or cost. Algorithms can vary vastly in size because of the amount of complexity, and amount of subroutines occurring in one algorithm. Capers Jones' Feature Point model is based on the following equation (34:115):

Feature Points = 1AT + 4EI + 5EO + 4EQ + 7ILF + 7EIF
with a Complexity Adjustment
(EI) represents External Inputs
(EO) represents External Outputs
(EQ) represents External Inquiries
(ILF) represents Internal Logical Files
(EIF) represents External Interface Files
(AT) represents the number of Algorithms

This methodology is a potential breakthrough considering that real-time, embedded, and scientific software comprise 48% of U. S. software (65:4). In addition to the independent and significant variable of algorithmic complexity, the Feature Points equation lowers the empirical, function point weighting of the data file parameter (EI) since input/output operations are not as critical outside the MIS world (34:114).

Feature Points have not yet been validated (17:32). This may be caused by the unclear definition of an algorithm which does not lend itself to a clear counting methodology. By the developer's definition of an algorithm, "the number of algorithms and number of significant computational problems is the same" (65:20).

However, it is possible to provide valid estimates for real-time systems using function point based methods also. One study by Gaffney and

Werling, using a modified function point equation, achieved a greater than 94% correlation on lines of code estimation for nineteen aerospace (non-MIS) software systems (26:2-3). The function point equation used only the four "external" function point functional types: external inputs, external outputs, external inquiries, and external interface files. Internal logical files were not used in their research. After the four external function point types were counted, "their complexity [was] ascertained as low, medium, or high. Then they [were] weighted correspondingly and then summed to determine the 'function count'. The next step in the calculation of function points [was] to determine the 'value adjustment factor'. . . . Finally, the 'function point' count [was] calculated by multiplying the 'function count' by the 'value adjustment factor'." (26:2) In this one case, the use of function point based methods appear to be valid for real-time systems as well.

Mark (Mk) II Function Points

Charles Symons of Nolan, Norton, & Company in London announced the Mark II Function Point Metric in 1983 in England. The Mark II metric was not well known in the United States until January 1988 when the description was published in the *IEEE Transactions on Software Engineering*. The impetus for this new metric was based on Symon's function point studies at Xerox. These studies lead him to four areas of concern surrounding the usage of Albrecht's function point model:

- He wanted to reduce the subjectivity in dealing with files by measuring entities and relationships among entities.

- He wanted to modify the function point approach so that it would create the same numeric totals regardless of whether an application was implemented as a single system or as a set of related subsystems.

- He wanted to change the fundamental rationale for function points away from value to users and switch it to the effort required to produce the functionality.

- He felt that the 14 influential factors cited by Albrecht and IBM were insufficient, and so he added six factors (34:96).

According to Symons, "the Mk II Function Point Analysis Method was designed to achieve the same objectives as those of Allan Albrecht, and to follow his structure as far as possible, but to overcome the weaknesses outlined above" (67:22).

In Symons model, Albrecht's five function point function types- external inputs, external outputs, external interfaces, external enquiries, and internal logical files- are replaced by "a collection of logical transactions, with each transaction consisting of an input, process, and output component. A logical transaction type define as a unique input/process/output combination triggered by a unique event of interest to the user, or a need to retrieve information" (67:23). These logical transactions consist of three types: number of input data element-types, number entity-types referenced and the number of output data element-types. An entity is "anything in the real world (object, transaction, time-period, etc, tangible or intangible, and groups or classes thereof) about which we want to know information. For example, in a personnel system 'employee' is an entity. 'Date of birth', however, is not." (67:53) The number of input data element-types and output data element-types mirror those similar measures in the Albrecht

function point model (67:70). An unadjusted function point (UFP) is determined by weighting each of these factors as seen in the below equation:

$$
\begin{aligned}
UFP's = W_I &* (\text{\# of input data element-types}) \\
+ W_E &* (\text{\# of entity-types referenced}) \\
+ W_O &* (\text{\# of output data element-types})
\end{aligned}
$$

(67:23)

Based on industry averages, the value of each of these weights are W_I=0.58, W_E=1.66, and W_O=0.26 (67:30). Once the unadjusted function point count is derived, it is multiplied by a technical complexity adjustment (TCA) to compute the Mk II function point total. The TCA factor consists of a technical complexity factor multiplied by a calibration factor, C. The TCA is computed using the following equation:

$$TCA = 0.65 + C*(\text{Total Degree of Influence})$$

(67:27)

The Total Degree of Influence mirrors the Albrecht function point Value Adjustment Factor. It has the original factors from Albrecht's model and five additional [value adjustment] factors:

- Interfaces to other applications
- Special security features
- Direct access requirement
- Special user training facilities
- Documentation requirements.

(67:26)

The calibration factor, C is derived from the ratio of work-hours to perform the technical complexity factors (Y) to work-hours for information processing size (X) (67:28). Figure 3 provides a general overview of the Mk II Function Point Method.

The relative worth of the Mark II Function Points has been compared to Albrecht's original function point model. The purported advantages of Symons model are that it is more objective than Albrecht's function points, it is easier to count via automated counting tools, and it is standardized in the United Kingdom (18:6). Symons claims that Albrecht's function points are not highly correlated to lines of code. He also contends that the Mark II

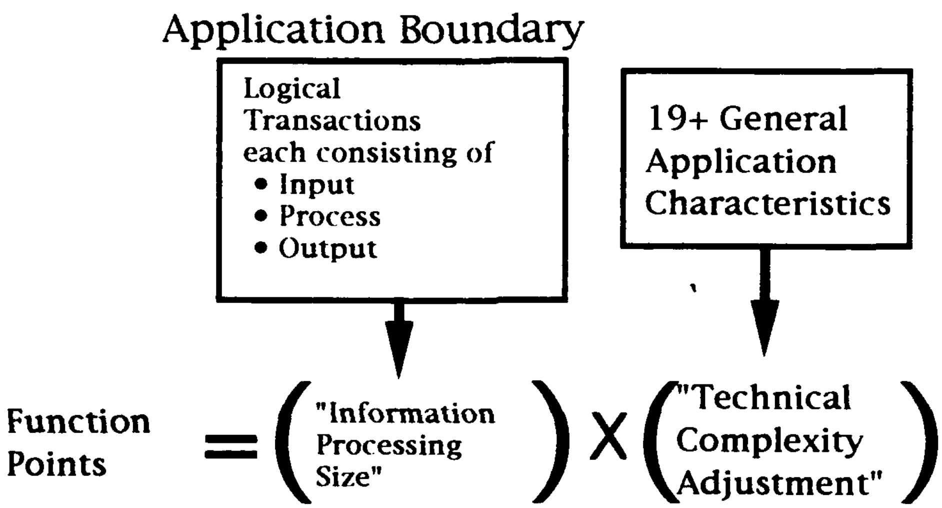


Figure 3. Components of the Mark II Function Point Method

(66:22)

Function Points are not highly correlated to Albrecht's function point counts on sample programs. However, the depictions of the scatterplots in the Symon's book do not support these assertions (67:35-36). Since there are no numbers to support/detract from either method in the book, the reader is still unclear as to their utility. According to Capers Jones, the developer of Feature Points, "when counting the same application, the resulting function point totals differ between the IBM [Albrecht's] and Mark II by sometimes

more than 30 percent, with the Mark II technique usually generating the larger totals" (34:96). Once again, the reader is only left to supposition in assessing this information since no quantifications are given. Jones does prefer Albrecht's function points to the Mark II concept because "function points measure the size of the features in an application that users care about" (34:97).

Synopsis of Literature Review

The literature shows that SLOC is a well-established, good estimator of effort. The major problem with SLOC models is determining SLOC early in the development program. Additionally, function point counting is a valid software estimating technique in industry. One way to make use of SLOC models and overcome its major problem is to use function points to estimate SLOC. Then, the predicted SLOC can be used as an input into SLOC models to estimate the level of effort in cost or man-months.

This review has also shown the need for effective management of software projects by first establishing the current position in the project. Also, effective measurement comes only from using effective measurement tools. Through calibration, function point estimation models can be even more accurate estimators. With 48% of U. S. software being comprised of systems, embedded, and real-time software, software managers could benefit by using and validating an estimation system that accounts for the number of algorithms included in these applications. A study of Feature Points as a tool could prove beneficial to software project managers and cost estimators. Also, the use of Mark II Function Points seems to hold some promise yet data in this area is rather sparse. Since it is an upgrade to the

Albrecht function point model, it could provide better estimates. However, this also could make for a good possible validation study.

III. Methodology

Introduction

This chapter presents the procedures to be used in gathering and analyzing data to answer the research question noted in Chapter I. The first section will provide an explanation of the method and research design to be used. The following section will provide a description of the data. This is followed by a section discussing the statistical techniques to be employed in the analysis.

Explanation of Method and Research Design

As of September 1991, a database of completed Air Force management information systems (MIS)/automatic data processing (ADP) projects with function point count information did not exist. As mentioned above, the information was available but had never been collected in a database, much less a database with all the necessary information to derive a complete function point estimate. In their efforts to become a center of expertise in MIS/ADP projects for the Air Force, the Standard Systems Center (SSC) has collected this function point information in the Software Process Database System (SPDS) database. In implementing function points, the SSC used the function point counting criteria set by the International Function Point Users Group (IFPUG) rather than a function point counting methodology included with a software package or published elsewhere (42).

Addressing the Investigative Questions

The road map for the methodology is included in the investigative questions from chapter one. The thesis will use a standard modeling approach to determine whether a relationship exists between function points and SLOC in order to address the investigative questions. The answers to these questions will give some indication as to how well function points values predict SLOC for MIS/ADP projects. The modeling steps to be followed in this methodology are as follows: identify drivers, specify the functional relationship between the drivers and the dependent variable, gather data, construct a model, and validate the model. Each of the modeling steps are executed for each of the individual investigative questions.

The case has been built that function points should be used to predict effort on software projects. Refer to Figure 4.

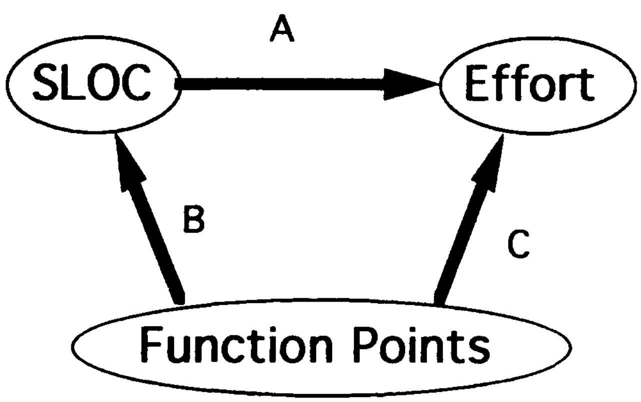


Figure 4. Thesis Modeling Concept

The hypothesis is depicted in B above. In the literature review, it was established that SLOC has historically been a good predictor of effort, as seen in relationship A in Figure 4 above. The problem with relationship A is that

SLOC is not easily determined in the early phases of a program. One solution is to use function points to predict SLOC, as seen in relationship B. Then, use predicted SLOC to predict effort as in relationship A. Note that "$\wedge$" is used to denote a predicted value based on the regression equation.

$$\widehat{\text{SLOC}} = f\,(\text{Function Points}) \tag{1}$$

then

$$\widehat{\text{Effort}} = f\,(\widehat{\text{SLOC}}) \tag{2}$$

This two step process may seem cumbersome at first. Many might query as to why the research does not simply use function points to predict effort, as seen in the below relationship.

$$\widehat{\text{Effort}} = f\,(\text{Function Points}) \tag{3}$$

There are a number of reasons to predict the number of SLOC from function points instead. As previously discussed, there are numerous commercial software models that already exist that model relationship A in Figure 4. Because there are less function point-based models, and function point estimation came into existence after SLOC-based models, less is known about function point usage. Therefore, this research is valuable because it might yield a method to obtain better estimates from the established SLOC-based

models. Finally, the data does not exist to support the development of a model of the form in (3) for Air Force MIS/ADP systems.

Discussion of Investigative Questions

Investigative Question I (IQI): How well do function point values predict SLOC for Air Force MIS/ADP projects?

As stated earlier, this thesis will use a standard modeling approach to determine whether a relationship exists between function points and SLOC in order to address the investigative questions. There are several subquestions which bear on answering this investigative question concerning the military data. Each of these individual subquestions for the military data will be annotated by "IQI" followed by an assigned letter designator. For example, the second subquestion to answer investigative question one will be designated "IQIb". The modeling methodology delineated below will be used as the basis for answering each of the investigative questions.

Military Database Investigative Questions

Investigative Question Ia (IQIa): How well do adjusted function points predict SLOC in the military environment?

As a reminder, adjusted function points, simply called function points, are the unadjusted function point counts multiplied by their value adjustment factor. The equation is represented in equation (1) above. The independent variable will be adjusted function points, and the dependent variable will be SLOC. Function point count information is provided in the SPDS database (Table 11).

Investigative Question Ib (IQIb): How well do unadjusted function points predict SLOC in the military environment?

IQIb assesses the relationship between the unadjusted function point count and SLOC. As discussed in the literature review, one of the strengths of function points is that it can be applied early in a software project. The unadjusted function point information comes from the requirements document. The Value Adjustment Factor (VAF) is based on 14 general system complexity characteristics, such as reusability of code, operational ease to the user, or the design of the software to facilitate change. Since this type of information may not be available in the earliest stages of the program, unadjusted function points may be a better predictor of SLOC. Additionally, Kemerer research showed that unadjusted function points had a higher correlation to SLOC than adjusted function point counts (44:425). The relationship is represented by equation (4) below.

$$\widehat{SLOC} = f\ (\text{Unadjusted Function Points}) \qquad (4)$$

The independent variable will be unadjusted function points, and the dependent variable will be SLOC.

Investigative Question Ic (IQIc): How well do external function points predict SLOC in the military environment?

IQIc assesses the relationship between external function points and SLOC. As discussed in the literature review, a study by Gaffney and Werling, using a modified function point equation, achieved a greater-than-94% correlation on lines of code estimation for nineteen aerospace (non-MIS) software systems (26:2-3). The function point equation used only the four

"external" function point functional types: external inputs, external outputs, external inquiries, and external interface files. Internal logical files were not used in their research. After the four external function point types were counted, "their complexity [was] ascertained as low, medium, or high. Then they [were] weighted correspondingly and then summed to determine the 'function count'. The next step in the calculation of function points [was] to determine the 'value adjustment factor'. . . . Finally, the 'function point' count [was] calculated by multiplying the 'function count' by the 'value adjustment factor'." (26:2) The same technique will be used to determine external function points for this research. The relationship is represented in equation (5) below.

$$\widehat{SLOC} = f\ (\text{External Function Points}) \tag{5}$$

The independent variable will be external function points, and the dependent variable will be SLOC. External function points will be counted using the same procedure as function points, except only the total of the four external function point types will be multiplied by the VAF to obtain the total external function point count, as in the Gaffney and Werling study.

Investigative Question Id (IQId): To what degree is the relationship between function points and SLOC affected by language?

As discussed in the literature review, a number of function point experts feel that the ratio of SLOC per function point vary with the language that the software is coded in (15:136, 34:76, 61:164). Since there are few programs in the SPDS database coded in a single language other than COBOL and just under half of the programs in the SPDS are in COBOL, indicator

variables will be used to assess if there is a significant difference between the COBOL function point to SLOC predictions and the other mixed and single languages. Therefore, this procedure will test to see if there is a difference between the ability of function points to predict SLOC written in COBOL versus in another language. Of the 55 programs with function point information in the SPDS Database, 26 are written in COBOL, six are written in single, other languages, and 23 in a mixture of different languages. This indicator variable procedure will be described in detail later in this methodology chapter. The relationship is represented in equation (6) below.

$$\widehat{SLOC} = f\,(\text{Function Points, Language}) \tag{6}$$

The independent variables will be function points and language, and the dependent variable will be SLOC.

Investigative Question Ie (IQIe): To what degree is the relationship between function points and SLOC affected by program complexity?

As mentioned in the literature review, it has been suggested by experts such as Boehm, McCabe, and Jones that program complexity could affect effort (9:1465, 18, 34:237-241). In fact, the Boehm article suggests that unnecessary program complexity could increase effort (9:1465). There are two measures of complexity that will be used in this analysis, the VAF and the system obsolescence complexity rating, both included in the SPDS. The VAF is the complexity factor composed of the 14 areas outlined in Chapter 2 (34:64). Of the programs in SPDS with function point and unadjusted function point information, each also was subjectively assessed by the program managers, called automated data systems (ADS) managers.

These subjective complexity assessments were called system obsolescence complexity ratings. So as not to confuse the reader, this complexity rating will be referred to as the obsolescence factor for the remainder of the paper. Obsolescence is the "process by which property becomes useless, not because of physical deterioration, but because of changes outside the property, notably scientific or technological advances" (24:392). It is a summary of the obsolescence factors including:

hardware platform (possible rating of 0-3),
security level (possible rating of 0-3),
language used (possible rating of 0-4),
customer complexity (possible rating of 0-5),
inputs complexity (possible rating of 0-5),
output complexity (possible rating of 0-5),
interfacing system complexity (possible rating of 0-5),
type of system it is (possible rating of 0-3) and
type of database it is (possible rating of 0-3).

The complexity rating has a range of 0-36 (69). Additionally, unadjusted function points will be used in lieu of function points because function points consists of a product of unadjusted function points and the VAF. The relationship is represented in equation (7) below.

$$\widehat{SLOC} = f\,(UFP,\ Complexity) \tag{7}$$

The independent variables will be unadjusted function points, and either of the two measures of complexity. The dependent variable will be SLOC.

Investigative Question If (IQIf): To what degree is the relationship between function points and SLOC affected by program complexity and program language?

This relationship combines the relationships in (6) and (7). The relationship is represented in equation (8) below.

$$\widehat{SLOC} = f\ (UFP,\ Complexity,\ Language) \tag{8}$$

The independent variable will be unadjusted function points as affected by differing complexities and languages, and the dependent variable will be SLOC. Unadjusted function points are used because the VAF and obsolescence factor are included separately in the relationship as an explicit measure of complexity.

Investigative Question Ig (IQIg): Using all the available independent variables and interactions between these variables, what is the best predictive model of SLOC in the military environment?

While questions IQIa-f investigate the nature of the underlying relationship, this question seeks the best model for predicting SLOC. This model will consider all significant drivers of SLOC as independent variables and will use stepwise regression as a modeling tool.

Commercial Database Investigative Questions

Investigative Question II (IQII): Does the strength of the prediction relationship between function points and SLOC differ for Air Force and non-Air Force projects?

The source of data to answer this question is found in the AFIT thesis entitled, *A Comparative Study of the Reliability of Function Point Analysis in Software Development Effort Estimation Models* by Robert B. Gurner (30:15-17). Function point count information is provided in the commercial

database. Although Gurner used the data to validate how well function points predict effort in man-months, the function point and SLOC data from his research will be used in this research. The data originally comes from two separate databases of MIS projects used to validate early function point usage (2:639-648, 44:416-429). This data is discussed later in this chapter and is displayed in Table 12, Appendix B. The basic methodology to address this investigative question will closely follow the methodology used to address the first investigative question.

Investigative Question IIa (IQIIa): How well do adjusted function points predict SLOC in the commercial environment? The relationship is represented by equation (9) below.

$$\widehat{SLOC} = f \text{ (Function Points)} \tag{9}$$

The independent variable will be function points, and the dependent variable will be SLOC.

Investigative Question IIb (IQIIb): How well do unadjusted function points predict SLOC in the commercial environment? The relationship is represented by equation (10) below.

$$\widehat{SLOC} = f \text{ (Unadjusted Function Points)} \tag{10}$$

The independent variable will be unadjusted function points, and the dependent variable will be SLOC.

Investigative Question IIc (IQIIc): To what degree is the relationship between function points and SLOC affected by language? The relationship is represented in equation (11) below.

$$\widehat{SLOC} = f\ (\text{Function Points, Language}) \qquad (11)$$

The independent variables will be function points and language, and the dependent variable will be SLOC. Since all of the programs in the commercial database are coded in a single language, indicator variables will be used to assess if there is a significant difference between the COBOL function point to SLOC predictions and the other languages. Therefore, this procedure will test to see if there is a difference between the ability of function points to predict SLOC written in COBOL versus in another language. Of the 39 programs with function point information, 31 are written in COBOL, four in PL/1, two in DMS, one in BLISS, and one in NATURAL.

Investigative Question IId (IQIId): To what degree is the relationship between function points and SLOC affected by complexity? The relationship is represented in equation (12) below.

$$\widehat{SLOC} = f\ (\text{Function Points, Complexity}) \qquad (12)$$

The independent variables will be function points and complexity, and the dependent variable will be SLOC. The measure of complexity that will be used in the analysis is the VAF. The Obsolescence factor is not available for this data set.

Investigative Question IIe (IQIIe): To what degree is the relationship between function points and SLOC affected by program complexity and program language in the commercial environment? This relationship combines the relationships in (11) and (12). The relationship is represented in equation (13) below.

$$\widehat{SLOC} = f\,(UFP,\ Complexity,\ Language) \tag{13}$$

The independent variables will be unadjusted function points, VAF, and language. The dependent variable will be SLOC. As before, unadjusted function points are used because the VAF is included separately in the relationship as an explicit measure of complexity.

Investigative Question IIf (IQIIf): Using all the available independent variables and interactions between these variables, what is the best predictive model of SLOC in the commercial environment?

While questions IQIIa-e investigate the nature of the underlying relationship, this question seeks the best model for predicting SLOC. This model will consider all significant drivers of SLOC as independent variables and will use stepwise regression as a modeling tool.

Investigative Question III (IQIII): How well do function point-to-SLOC conversion tables created from Air Force and commercial data compare to function point-to-SLOC conversion tables provided by industry experts?

To address this question, regression using only the 26 COBOL programs will be applied to test the relationship between function points and COBOL SLOC using the military database. The test is limited to only the COBOL

programs because that is the only single language with enough programs, 26, to be considered a statistically valid sample. The regression will be run to model the relationship without controlling the y-intercept as well as with setting the y-intercept to zero. The function point-to-SLOC conversion tables reflect a linear relationship in which the Y-intercept is set to zero. By including the regression with the y-intercept, a comparison to the forced y-intercept of zero is possible. These ANOVA tables help to validate the merit of the SLOC to function point conversion tables, at least for COBOL. A similar analysis will be used to test the 31 COBOL programs in the commercial database. Additionally, an analysis of the answers to investigative questions IQId and IQIIc will be included. These are the questions that determine the degree of the relationship between function points and SLOC is affected by language. While the data is limited, there is an adequate number of COBOL programs to make an assessment of that portion of the conversion tables.

Modeling Methodology

This portion of the chapter will describe the methodology involved in developing parametric models to capture the SLOC prediction estimates of the above investigative questions. As appropriate, each of the above relationships will be modeled in a single independent variable (SIV) relationship or a multiple independent variable (MIV) relationship. Using SAS, a statistical analysis software package available on the Air Force Institute of Technology (AFIT) VAX computer system, these SIV and MIV models will be developed using linear regression. The discussion below provides specific procedures and techniques to develop and validate the models. The techniques mentioned below are from the COST 671 (*Defense*

Cost Modeling) and COST 672 (*Model Diagnostics*) courses taught at AFIT (50,51). These were synopsized in *A Model for Estimating Aircraft Recoverable Spares Annual Costs* by Phillip L. Redding (59). This methodology section of this thesis will closely follow portions of Redding's work except where information pertaining specifically to this research is concerned. Each of the steps involved in developing the above SLOC estimating relationships are provided below as a general framework.

Step 1-Identify Cost Drivers. The identification problem is one of identifying the major factors that affect/influence the amount of SLOC of a project. This was accomplished to a large extent in the first portion of this chapter. The first step is to define the population. The population is limited to the MIS/ADP environment because research has shown that function points are more effective in the MIS/ADP environment (13:559, 44:422). With the system's definition and purpose in mind, the system can be characterized using physical and performance characteristics. By restricting the population to MIS/ADP, it is easier to identify the major factors affecting SLOC. The purpose of this step is to identify important factors for the model that actually cause SLOC to either increase or decrease. Although there are numerous factors, such as ability/experience of the programmer, mood of the programmer, and the use of automatic programming tools that could influence the amount of SLOC in a program; it is hypothesized that the factors outlined in the previous section are the determinants of the eventual effort required for the MIS/ADP programs.

There is even more to model identification according to Redding.

> A specific consideration under the general 'model identification' heading is testing for interaction effects and indicator variables. . . . If

one changes the value of an independent variable and the resulting change in cost is dependent upon the value of another independent variable, there is an 'interaction effect' between the independent variables (59:60).

For example, if the change in SLOC related to a change in function points also depends on complexity of the program, there is interaction between these two variables. Function points and complexity were tested for an interaction effect, along with function points and language. By multiplying the variables by each other in each of the above pairs, the resultant products became new independent variables.

"Indicator variables are used to determine if the sample population can be divided into separate classes based upon qualitative differences" (59:60). In terms of this thesis, the class variable introduced is language. Indicator variables were included to determine if SLOC is related to the following classes of software programming language: 1) COBOL or 2) other. Of the 55 programs with function point information in the SPDS database, 26 were written strictly in COBOL, 6 were written in single other languages, and 23 were written in mixed languages. Of the 39 programs with function point information in the commercial program database, 31 are written in COBOL, four in PL/1, two in DMS, one in BLISS, and one in NATURAL. For the purposes of this study, the indicator variable for language reflects that the systems were either COBOL or "other".

Step II-Specify Functional Form of the Estimating Relationship. When trying to assess how SLOC will respond to a change in function points, specification distinguishes the nature of the relationship. This step involves hypothesizing the expected relationships between the dependent variable (SLOC) and various independent variables (IVs). An example would be to

hypothesize that the relationship between the IV and DV is either linear or non-linear. The first and second derivatives of the SLOC estimating function will characterize the relationship within the relevant range of the function between IVs and SLOC. The application of linear regression will lead to the most accurate and reliable estimate of the population regression line only if the underlying relationship is linear. If the relationship is nonlinear, the regression line will not provide accurate estimates unless the data is transformed. Identification of the relevant range, where the model is applicable, will ensure that the model will be useful for the input data. The further from the mean, the less accurate the regression line will be.

When specifying the model, one should ensure that the model makes logical sense. For example, it makes logical sense that as the amount of functionality of a program increases (reflected in function points), the SLOC of the program will increase. As alluded to earlier, the expectation is to see a positive relationship between the independent variable, function points, and the dependent variable (DV), SLOC. This contention is supported by fact that experts feel that lines of code increase as functionality increases (2:639, 17:31). Therefore, it is expected that the first derivative of the function between adjusted function points and SLOC will be positive. The first derivative is a measure reflecting the slope of the function. The second derivative determines whether the slope is constant, increasing, or decreasing. Some experts contend that the relationship is a linear one (15:136, 34:76, 61:164, 49). This is seen in the discussion pertaining to function point to SLOC conversion tables. This implies a zero second derivative. Symbolically, this situation is represented by the notation, (+, 0). This research accepts the hypothesis that the linear single independent

variable (SIV) model could be represented by a (+, 0) relationship. However, each of the three possible transformations of each of the IVs that have a positive first derivative, (+,+), (+,-), or (+,0) will be assessed via residual plot analysis (discussed below). These three relationships are represented below in Figure 5. An article by Boehm suggests that unnecessary program complexity could increase effort (9:1465). This could imply a (+,+) relationship as complexity increases.

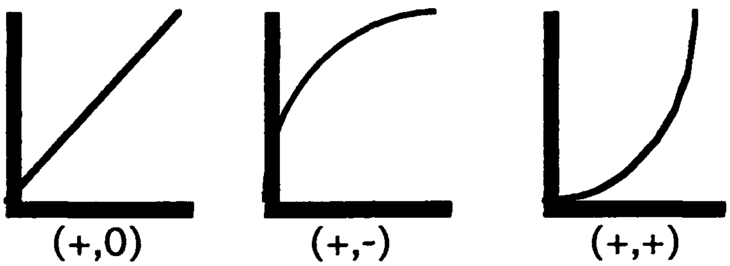


Figure 5. 1st and 2nd Derivatives of a Function

Because SAS can only work with linear relationships, the data is transformed to investigate nonlinear relationships. Transformation of the variable occurs by setting the independent variable equal to itself raised to a power thereby the relationship would be linear as transformed. The initial SAS runs were made using the presumed linear independent variables. Additional runs were then performed based upon the results of this initial analysis (59:64-65).

Since the experts generally agree that the SIV model would yield a (+,0) relationship, this will be the first model to be investigated. There is another check to see if the models are properly specified. In SAS, the difference between the observed values and the predicted values derived from the regression equation can be calculated. These differences are called

residuals. SAS allows the residual values to be plotted against the independent variable data. By examining the residual plots for patterns in the data, the need for a transformation of the independent variable can be assessed. If the residual plot information appears random, then one may assume that the model is properly specified, and no transformation of the data is required (59:69-70).

This information would be used to assess if the relationship is a (+,+) or (+,-) curve. When discussing the these functions, the SIV model follows the below relationship:

$$\hat{Y} = b_0 + b_1 X^k$$

For a (+,+) relationship, the parameter values are $b_1 > 0$ and $k > 1$ (example is $y=x^2$). Transforming the IV to e^x has also been recommended (52:143). The (+,+) relationship is also seen in logarithmic transformations of the both the independent and dependent variables simultaneously, known as "ln-ln" transformations. For a (+,-) relationship, the parameter values are $b_1 < 0$ and $k < 0$ (examples are $y=x^{-1}$ $y=x^{-1/2}$) or $b_1 > 0$ and $0 < k < 1$ (example is $y=x^{1/2}$). For a (+,0) relationship, $b_1 > 1$ and $k = 1$ holds true (example is $y=3x$).

The residual plots will also provide information pertaining to heteroscedasticity of the data. "The condition of error variance not being constant over all cases is called heteroscedasticity" and is a violation of the assumptions of regression modeling (52:423). Heteroscedasticity would be readily apparent if the residuals become larger or smaller as the function point (DV) measure becomes larger. To combat heteroscedasticity, a logarithmic transformation of the dependent variable is recommended (51, 52:146).

Step III-Collect and Normalize Data. This step involves collecting and normalizing the data needed to investigate the proposed model. The military function point information to be analyzed came from the Software Process Database System (SPDS) at the Air Force Standard System Center, Gunter AFB, AL. Information on the database was gathered through direct interviews of two personnel intimately familiar with its history, information therein, and capability/limitations. This information is described below.

In an interview on 23 March 1991 with Dub Jones, the most knowledgeable person about the development of the SPDS, he provided the following description of SPDS: The database contains the following information: adjusted function point counts, unadjusted function point counts, 14 general application characteristics, and the computed value adjustment count for each case. Also, it contains the following information: actual project SLOC, pages of documentation, and the five components of the function point count (external inputs, external inquiries, external outputs, internal logical files and external interface files). These components are given low, average, or high ratings which lead to the unadjusted function count. The methodology used to derive the function point related information used the IFPUG Function Point Counting Practices Manual, Release 3.3 as well as training sessions by a support contractor, Productivity Management Group (PMG). The database has read/write privilege protection. Only ADS managers have write privileges. An important point to note is that the function point counts in the database were performed after the programs were completed, not prior to the start of work.

The second database consisting of commercial business programs is an aggregate of two industry-based function point databases that had been

previously empirically validated with function point based counting methodologies were used in the validation of SPANS, Checkpoint, and Costar in a thesis by Gurner (30:15-26). Both databases will be used in this thesis. The first 24 programs in the commercial function point database used in this thesis originated from a study by Albrecht and Gaffney that validated function point usage in 1983 (2:640). The second 15 programs in the commercial function point database used in this thesis originated from a study in 1987 by Kemerer that further validated function point usage (44:421-424).

Normalization refers to adjusting the data for any anomalies. An anomaly is anything that distorts the data. The purpose of normalization is to capture the true underlying relationship after removing the anomalous effects. For example, normalizing could involve placing different year dollar values into a common year equivalent by taking inflation into account. There is no dollar information on the programs taken from SPDS. However, the data was checked for internal validity by ensuring that the function point values in the SPDS were derived from the Value Adjustment Factor (VAF) and the unadjusted function point count. Additionally, VAF was checked to ensure that it calculated correctly from the 14 program characteristic degrees of influence. Also, the SPDS data was collected by individuals with the program development offices, then checked and reported by the individual automated data system (ADS) managers. When performing the function point counts, the personnel involved were knowledgeable in function point counting procedures using a standardized methodology, the IFPUG Function Point Counting Practices Manual, Release 3.3. In fact the Standard Systems Center, keeper of the SPDS database,

enlisted the aid of a contractor, Productivity Management Group (PMG), Inc., to implement proper counting practices. Some of the function point counts are performed by PMG, some performed with PMG oversight, and some had been totally transitioned to SSC personnel once the SSC personnel had been fully trained. Therefore, it seems safe to assume that the SPDS function point data is free of errors (39).

Dub Jones did advance a number of possible problems with information in the database. First, actual line of code counting methods differ between systems. As in industry, there are different interpretations of a line of code. For example, some personnel only count executable source lines of code while others include comment lines in programs. Also, some of the ADS offices used automated code counters while others did not. Second, possible different levels of training of function point counters and lack of accessibility to "experts" for function point information in the development offices may taint information. Third, there may be a risk that personnel providing counts may expand function point counts as large as possible to enhance their own productivity levels as reported to their supervisors (39).

The initial analysis, derived from the first stepwise regression equation, yielded the obsolescence complexity factor as a significant variable selected for the model. The author is choosing to not use the obsolescence complexity factor variable in the analysis. There are numerous reasons for this decision. First, the obsolescence complexity factor is subjectively assessed by the ADS managers at Gunter Air Force Base on nine obsolescence complexity factors. The lack of a more detailed and robust criteria causes doubt as to its validity as a measure of complexity. The criteria for selection do not seem rigorous enough at this point in time. Second, the obsolescence

complexity factor is not a standardized term in function point knowledgeable groups like the Value Adjustment Factor is. One of the purposes of this research is to provide useful information to potential users of function point measures. Since the obsolescence complexity factor is only used by personnel at Gunter AFB from the detailed literature review, it is subjectively assessed that this measure is too obscure to be useful. Third, the data seem to show that this factor estimates KSLOC too well which causes doubt as to its validity. The obsolescence complexity factor is correlated to KSLOC at the 0.5726 level. Additionally, in most of the above models, the obsolescence factor (OBSOL) came in at the 99.9% level of significance. Additionally, the obsolescence complexity factor is not highly correlated to the well established complexity factor of VAF, implying that it may not necessarily measure complexity as is understood by the function point community. Table 2 depicts these relationships.

Table 2. Correlation Analysis of VAF to Obsolescence Factor

CORR	VAF	OBSOL
KSLOC	0.4835	0.5726
FP	0.3748	0.4045
UFP	0.3806	0.4078
VAF	1.0000	0.4938
OBSOL	0.4938	1.0000

For all these reasons, the obsolescence complexity factor variable has been eliminated from inclusion in the final model.

Step IV-Calculate Parameter Estimates. In this step, SIV and MIV model are constructed with the dependent variable being SLOC. This step involves "actually using SAS to specify the relationship between the

dependent and independent variables in mathematical terms. A regression line is fit to the data via SAS using the method of least squares best fit" (59:64). Each regression line is expressed in the following equation form:

$$Y_i = B_0 + B_1X_{i1} + B_2X_{i2} + \ldots + B_{p-1}X_{i,p-1} + e_i \tag{14}$$

where

$B_0, B_1, \ldots, B_{p-1}$ are parameters $\quad X_{i1}, X_{i2}, \ldots, X_{i,p-1}$ are known constants

e_i are independent $N(0, \sigma^2)$ $\quad i = 1, \ldots, n$

(52:229)

Note that the B_j's are estimates of the influence of an explanatory variable on the dependent variable. Using the concept of LSBF modeling, these values for B_x are determined via SAS using LSBF modeling concepts. For example, if Y_i represents an estimate of the number of KSLOC (thousand lines of SLOC) and X_{i1} represents function points, B_0 would be the LSBF y-intercept and B_1 would be the estimate of the influence function points has on KSLOC.

The possible models were fit by estimating parameter values using LSBF on the transformed data if applicable. These SAS data runs will provide all the standard regression equation information to include an ANOVA table, R^2, slope, intercept, F, t, p, and confidence interval information.

Prior to equation formulation, a discussion of how to handle the different classes of language used on each of the programs is needed. By reviewing the database, it is clear that programming language used could affect function point estimates because of the differing levels of this qualitative attribute. "A treatment corresponds to a factor level (53:524)" . The treatments in this research are the two categories of language (COBOL or Other). To explain factor level, "a level of a factor is a particular form of that

factor. . . . in a study of the effect of color of the questionnaire paper on response rate in a mail survey, color of paper is the factor under study, and each different color used is a level of that factor (53:523)". "The treatments included should be able to provide some insights into the mechanism underlying the phenomenon under study (53:525)".

This is important, because once the data is regressed based on each treatment type, the regression lines from the basic IV-DV relationship depending on the class of the treatment effect may differ in slope and intercept. Potential example is depicted below in Figure 6 based on the language treatment effect. Note that differing treatments can change the slope and the Y-intercept of the regression line if there is a significant difference between language types.

Each of the investigative questions will be restated in a format similar to equation (14) above. The independent variable (IV) in each of the equations is one of the various function point measures, represented by X. The dependent variable in each case will be an estimate of SLOC, in KSLOC, represented by Y-hat, the predicted value of Y. The basic equation that will model the relationship depicted in equation (3) for IQIa is as follows:

$$\hat{Y} = B_0 + B_1 X \qquad (15)$$

where X = the adjusted function points from the SPDS database.

The basic equation that will model the relationship depicted in equation (4) for IQIb is as follows:

$$\hat{Y} = B_0 + B_1 X \qquad (16)$$

where X = the unadjusted function points from the SPDS database.

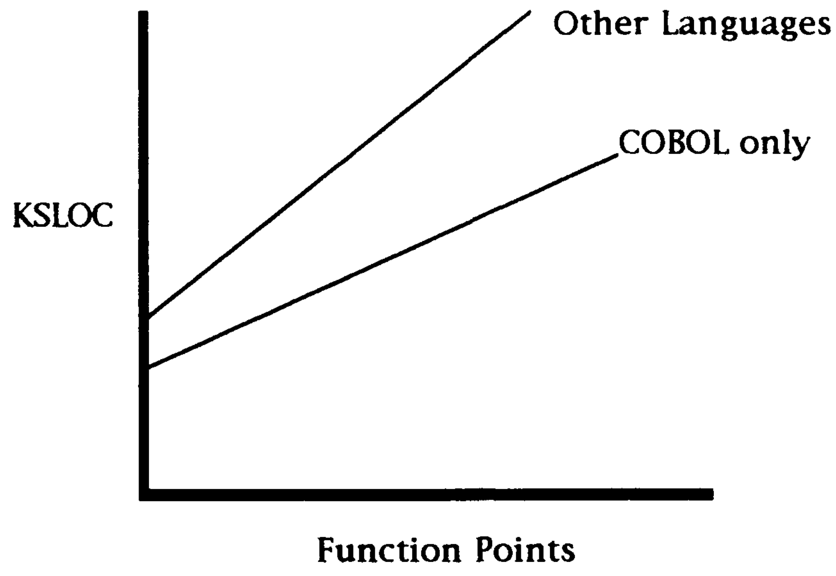


Figure 6. Treatment Effects on the Regression Equation

The basic equation that will model the relationship depicted in equation (5) for IQIc is as follows:

$$\hat{Y} = B_0 + B_1 X \tag{17}$$

where X = the "external" function points from the SPDS database.

The basic equation that will address all the possible permutations of complexity and the language indicator variables are as follows:

$$
\begin{aligned}
\hat{Y} = {} & B_0 + B_1X && \text{(accounts for adjusted function point or unadjusted portion)} \\
& + B_2V + B_3VX && \text{(accounts for complexity effects)} \\
& + B_4L + B_5LX && \text{(accounts for language effects)} \\
& + B_6VL + B_7V(L)X && \text{(accounts for interaction effects between language and complexity)}
\end{aligned} \tag{18}
$$

Where V is the value adjustment factor, and L is the language indicator factor.

Step V-Validate the Model. This step validates the model. This step involved using model diagnostics which can be performed to check a model's internal validity (see below). This is accomplished by assessing the analysis of variance (ANOVA) table containing many statistics for evaluating the model. The ANOVA table will yield information such as R^2, adjusted R^2, F-value and others (52:92-93). The format of the ANOVA table is provided in Table 3 below.

There are a number of factors that must be evaluated to ensure that the correct final estimating relationship between the dependent variable, DV and the independent variable, IV is chosen. The first factor to ascertain is if the signs of the parameter estimates are supported by logic. For example, the expectation is to observe a positive B_1 since logic and the experts agree that there is a positive relationship between a program's functionality and size in SLOC. Next, the values from the ANOVA table will be used to determine the overall predictive strength of the model. Each of these is discussed below.

> The coefficient of determination (R^2) measures the proportion of the total variability in the dependent random variable which is explained by the independent variables through the fitting of the regression line or the percentage of total squared error accounted for by the regression line. The closer R^2 is to 1.0, the stronger the relationship between the random dependent variable and the independent variable in the selected model. The R^2 measures the strength of the relationship between the variables (59:67).

TABLE 3

ANOVA Table Format (SAS)

Source of Error	Degrees of Freedom	Sum of Squared Error	Mean Squared Error	F-Value	P-Value
Model (R)	P-1	$SSR=\Sigma(\hat{Y} - \bar{Y})^2$	MSR=SSR/df	MSR/MSE	*
Error (E)	n-P	$SSE=\Sigma(\hat{Y} - \bar{Y})^2$	MSE=SSE/df		
Total (T)	n-1	$SST=\Sigma(\hat{Y} - \bar{Y})^2$	MST=SST/df		

Root MSE	*	R-squared	*
Dep Mean	*	Adj R-sq	*
C.V.	*		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for HO: Parameter=0	Prob>{T}
Intercept	*	*	*	*	*
Driver#1	*	*	*	*	*
Driver#2	*	*	*	*	*
Driver#3	*	*	*	*	*

Where

$\hat{Y}_i$ = the ith fitted value on the regression line

$\bar{Y}$= the mean of the observed values in sample set

Y_i = the ith observation from the sample set

P = the number of parameters in the model

n = the number of observations in the sample set

* denotes actual numerical values in actual SAS output

For this research, an R^2 of 80% or greater is preferred with an acceptance threshold of no less than 70%. Note that the R^2 value can be artificially driven higher by increasing the number of independent variables whether they are valid SLOC drivers or not. To combat this possibility, the adjusted R^2 was compared to the adjusted R^2 value. If both values are not within 20% of one another, it can be assumed that insignificant variables are present within the model and are affecting the R^2 (59:67)

The F-value significant at 70% or greater is a typical rule of thumb for acceptance (59, 50). An 80% or better is preferred in final model selection. This criteria will allow the determination of the statistical significance of the selected model. An F-value with a 95% confidence level tells us that the probability of rejecting a true null hypothesis (Type I error) is 5%. The F-value tests the null hypothesis, that the regression coefficients in the selected model are insignificant (equal to zero), against the alternative hypothesis that at least one of the regression coefficients, excluding the y-intercept, is significant (not equal to 0). An F-value calculated from the ANOVA table, based on the selected model, which exceeds the F-value from the F-distribution table will allow us to reject the null hypothesis. If the model is statistically significant, the F-value will mandate rejecting the null hypothesis and concluding that the compound effect of the independent variables in the selected model significantly impact the dependent random variable, cost.

The t-value significant at 70% or greater is a typical rule of thumb for acceptance (50, 59). An 80% or better is preferred in final independent variableselection. The t-value tests the individual significance of each independent variable as a SLOC driver. A t-value with a 95% confidence

level tells us that the probability of rejecting a true null hypothesis (Type I error) is 5%. The t-value tests the null hypothesis, that the regression coefficient of each individual variable in the selected model is insignificant (equal to 0), against the alternate hypothesis that the variable is significant (not equal to 0).; A t-value is calculated from the parameter estimates and its associated standard error. A t-value which exceeds the t-distribution table value will allow us to reject the null hypothesis and conclude that the individual independent variables in the selected model are significant cost drivers. On a SIV model, the t statistic squared and the F statistic are the same.

The p-value denotes the probability of getting an F_{ratio} as big as F_{calc} or larger when X and Y are truly independent. In other words, the p-value is "the smallest significance level at which the null hypothesis can be rejected" (54:357). For example, a p=.0077 says that you are 99.23% confident that the F_{ratio} was not just due to sampling error and the X and Y are really dependent. Therefore, the lower the p value, the better chance that there is a statistical relationship between X and Y. For comparison's within this research, the p-values will be used to show the significance of the F and t statistics since these statistics change with sample size. As pointed out above, by taking (1 - p-value) for each model and parameter, it will be easier to understand their level of significance.

Coefficient of Variation (CV) should be less than 50% (50, 59). Multiplying CV by two gives the 95% prediction bounds, in terms of percentage, around the center of the data (Y-bar) if Y is normally distributed. "For example, the coefficient of variation tells you that if you estimated at the center of your data, 2 * CV gives you the approximate

interval that the prediction may fall at the 95% level of confidence" (51). The smaller CV is, the greater the possibility of getting good estimates of the dependent variable at the center of the data. CV is calculated by the square root of the MSE divided by the Y-bar as seen below.

$$CV = S_{YX}/\overline{Y}$$

As significance parameters are include in the model, MSE will decrease. The square root of MSE is the standard error of the estimate and measures the absolute fit of the sample data points to the regression line, i.e., the variance of Y given X. As MSE decreases, CV decreases and the F-value increases. The CV is one tool that is currently available to me for comparison between the logarithmic and non-logarithmic models is the comparison between the non-logarithmic CV and the logarithmic S_{YX}. In the non-logarithmic case, the CV gives the size of the estimated error relative to the estimate. In the logarithmic case, the MSE yields the average percent squared estimating error. Therefore, the S_{YX} gives the average percent estimating error.

The chosen model, once shown to be significant, should have the highest R^2, highest F_{calc} (lowest p for the model), highest t_{calc} (lowest p for the variable), lowest MSE, lowest CV. Since the measures used above are only valid in comparisons between models with the same dependent variable, this step will narrow the selection to best model of the logarithmic and the best of the non-logarithmic possibilities.

The final portion of the analysis section will include a qualitative analysis for similarities and differences between the Air Force and industry databases. It will also discuss potential confounds in the collection of data,

i.e. improper function point counting methods. The qualitative portion of the study will only be able to be further refined once more information is known about the database, collection method, and outcome of the ANOVA comparison.

The answers to investigative questions IQIg and IQIIf provide the best predictive models of SLOC. To be useful, these models should be devoid of collinearity. To address these questions, collinearity is defined and discussed. Collinearity among significant SLOC drivers becomes a constraint on the use of the model. Collinearity can adversely effect a model. It can inflate the variances of the regression coefficients for model variables that are correlated to each other. These inflated variances could cause the regression coefficients to be unstable, have the wrong sign, or make significant variables become insignificant. Therefore, the interpretation of the regression coefficients is unclear (51).

To answer investigative questions IQIg and IQIIf, an interactive stepwise procedure is developed. The first step is to implement one of the stepwise regression tools in SAS coupled with collinearity analysis to obtain the "best" possible model devoid of collinearity. In this first step, all the possible combinations of the function point information that made sense, including interactions of two variables (e.g. FP * Lang). SAS has five different stepwise variable selection procedures. The one chosen for implementation is Maximum R^2 improvement (MAXR) procedure. This procedure focuses on selecting variables based on an examination of all pairwise interchanges of variables not already in the model. This process will result in the largest increase in R^2. The SAS text states that this procedure has the best chance of finding nearly optimal models (23:83).

Additionally, this procedure is chosen over a significance based procedure because initial data runs exhibited 99.9% significance levels but had lower R^2 values.

The specific technique to be used in employing the MAXR involves inputting all the possible variables and their interactions with other variables that made sense. The top six variable model would be used as a starting point. The reason for stopping at a six variable model is that some of the variables will begin to appear many times in interactive variables and by themselves implying collinearity was present. This is due to the fact that there were so few variables involved initially.

The next step is to implement the SAS COLLINOINT procedure. This performs "an eigenanalysis of matrices derived from the sums of squares and cross products of these variables" yielding analyses of relationships among a set of variables (23:81). For more detailed information on the theoretical specifics of eigenanalysis, the author suggests reading Chapter 3.2 in the book, *Regression Diagnostics* by David A. Belsey et al. A detailed discussion of collinearity diagnostics theory is beyond the scope of this research. Specifically, COLLINOINT will provide eigenvalues, condition numbers, and variance proportions. The closer to zero an eigen value is the more collinearity is present. The condition numbers reflect relationships between the eigen values. The rule of thumb is that if the condition number is greater than 10, the amount of collinearity in the model is significant. Once collinearity is determined to be present via the condition number, the variance proportion values can be calculated to determine which two independent variables are being affected by collinearity. For example, if COLLINOINT was performed on a model that displayed a condition number

greater than 10, the two variables that have the highest variance proportions (VAR PROP) have the most collinearity. Thus, one would have to be eliminated to mitigate collinearity (51).

The technique used is an iterative process. The author will find the best six variable model with the MAXR procedure. Then, COLLINOINT procedure will be performed on these six variables. If the condition number exceeds 10, then the highest two VAR PROPs variables will be run with the MAXR procedure to determine which will be dropped from the model. The highest R^2 variable for MAXR purposes is always kept. If there are more than one condition number out of bounds at a time, the highest condition number variables will be addressed first. The process will result in a condition number of less than ten.

Another topic that falls under model diagnostics is data outlier analysis. "Outliers are extreme observations. . . . Outliers are points that lie far beyond the scatter of the remaining residuals [in residual plots], perhaps four or more standard deviations from zero" (52:121). In the statistical analysis of the data, it is possible that a model may have a bad fit of the regression line through the data caused by an outlier. Even if the statistics indicate a good fit, a model's predictive capability could be low. This situation could also be caused by outlier data. Outliers may have large residuals, may have great impact on the regression function and resulting statistics, or may be extreme values. Extreme values will always appear as outliers simply because of their position in the data set. The hypothetical effects of an outlier on the regression line can be seen in Figure 7 below.

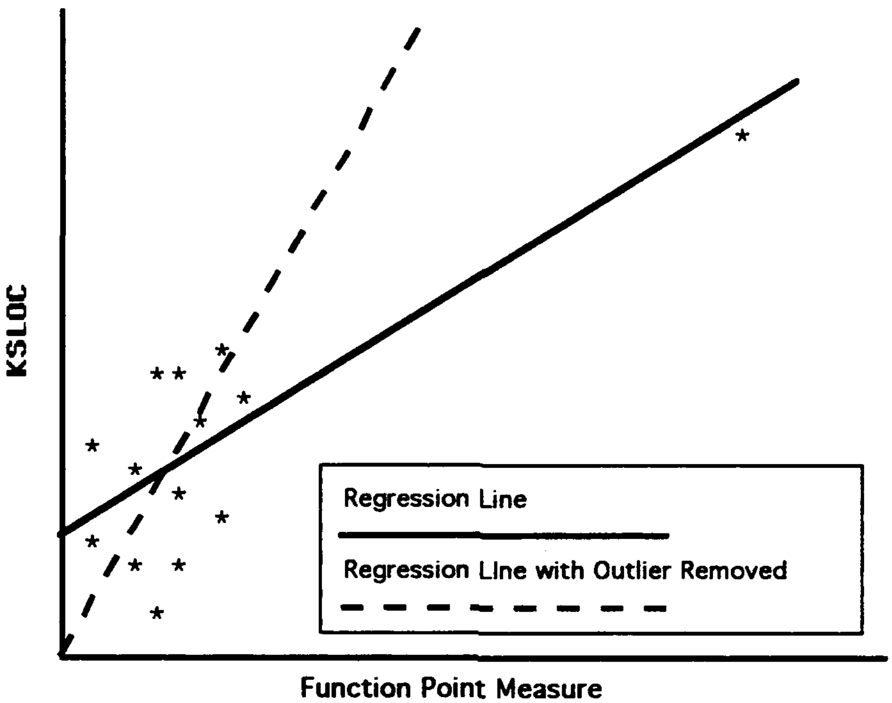


Figure 7. Outlier Effects on Regression Line

As is readily obvious from the Figure 7, the one outlier has "pulled" the regression line to a new slope and intercept. It is important to note that outliers with respect to Y will always impact the model but outliers with respect to X may or may not impact the model (51).

Outliers with respect to X. The first step in the analysis of outliers is to examine those observations that were outliers with respect to X. This is accomplished by analyzing the leverage values obtained from the Hat matrix. The Hat matrix is used to express the fitted values of Y-hat as linear combinations of the observed values of Y. The values that lie on the diagonal of the Hat matrix are called leverage values. These leverage values are used to indicate the distance between the X values for the individual observations and the means of the X values (independent variables). A large leverage value is indicative of an outlier. A rule of thumb used to determine potential

outliers was (2*p)/n, where p is the number of parameters including the intercept, and n is the number of observations. If the leverage value was greater than (2*p)/n, it was identified as an outlier with respect to X (51).

Outliers with respect to Y. An outlier with respect to Y is defined as an observation that the model doesn't predict very well. Possible causes include wrong population, incomplete model identification, incorrect model specification, data entry errors, and measurement errors. The studentized residual analysis is used to identify outliers with respect to Y. If the t-value is less than the absolute value of the system studentized residual it is identified as an outlier with respect to Y (51).

Influential Outliers. Once the potential outliers with respect to X and Y have been identified, the next step is to determine if these had a significant impact on the model. An outlier that is influential is one that affects the functional form of the fitted regression line. The three methods that will be used to identify the amount of influence of outliers are: the influence of the fitted values (DFFITS), the influence on the regression coefficients (DFBETAS), and Cook's distance test.

DFFITS is a measure of the influence that a system has on the predicted regression value of Y. The criteria used to determine the influence of an outlier is if the DFFITS absolute value is greater than 1, then the outlier is influential (51).

DFBETAS are based on the difference between individual regression coefficients for the models based on the data sets with and without that observation. The criteria is that systems with DFBETAS greater than one were considered potentially influential. DFBETAS greater than 1 suggest that

the observation has a large influence on the value of the regression coefficient estimates.

Cook's distance measure is an overall measure of the combined impact of the individual system on all of the estimated regression coefficients. If Cook's D is greater than F_{ratio} for a 0.5 alpha, it is indicative that it is an influential outlier.

Typically, if a data point is identified as an outlier, it is not deleted from the database unless it is determined that it is part of the wrong population as defined upfront in the research. Being an extreme value is not always enough to justify throwing out a datapoint. This is a subjective assessment on the part of the researcher (51).

IV. Analysis and Findings

Introduction

This chapter discusses the analysis and findings generated from the procedures described in Chapter III, "Methodology." The discussion is divided into five main sections. The first section, entitled "Initial Results," will present the statistical analysis to support the investigative questions in Chapter III. The second section, entitled "Outlier Analysis," discusses influential outliers with respect to X and Y. This section will provide details as to whether any of the programs in the databases should be deleted. The third section, entitled "Transformation Analysis," analyses and reviews the regression plots and residual plots in order to determine the need to transform the IVs and/or DV. The finalized "best" models for each database and the investigative questions will be addressed here. The fourth section, entitled "Function Point to SLOC Conversion," will summarize the results of the research on function point's ability to answer IQIII. The investigative question queried as to how well the function point-to-SLOC conversion information contained within the military and commercial databases compare to that same information provided by industry experts.

Initial Results (Military Database)

This section addresses how well function point measures can predict SLOC for both environments, military and commercial. Both sets of raw data can be found in Appendix B. The military database is listed in Table 11, and the commercial database is listed in Table 12. Each of the investigative questions is answered and the information from the ANOVA charts is

summarized in a table format according to the criteria mentioned in Chapter 3. For more detail, all ANOVA tables from which these charts were derived is placed in Appendix E.

The statistics resulting from fitting the models proposed in Chapter III are presented in Table 4 below. It should be noted that all of the models representing each of the investigative questions were found to have a 99.9% level of significance for the F-statistic as seen in the first column. You'll also note that in each model, except model I, the R^2 value far surpasses the 0.70 criteria. In addition, each of the coefficient's t-test significance levels are represented by p-values in brackets. The vast majority of them are significant at the 99.9% level of significance. At the onset, the reader might assume that all of these are good models because the models are highly significant; the coefficients are highly significant; and their measures of goodness of fit (R^2) are high. However, the reader will note that the measure of the predictive capability of the model (CV) fails well beyond the criteria of 50. From Chapter 3, note that the CV denotes the percentage error of the estimate at the center of the data.

This information shows that function point measures are a significant measure of SLOC providing a high goodness of fit but the variability in the data cause doubt as to its predictive capability. Model D shows that the coefficient for the language indicator variable (Lang) is significant at a 0.9865 confidence level. This indicates a significant difference between the predictive capability of models in one language (COBOL) versus other non-COBOL languages and mixed languages. Model E shows that the coefficient of the interaction of Lang and function points is significant also. However, when this interaction takes place, the coefficient for Lang becomes

insignificant. This happens because of collinearity between the two Lang terms as discussed in Chapter 3. In model F, the complexity factor of VAF is significant to the 99.9% level. In model G, the R^2 increases slightly with the inclusion of the interaction of UFP and VAF.

Table 4

ANOVA Results of Military Data, All Programs, Straight Linear Regression

Dependent Variable: Ln KSLOC				Coefficients (P-Value in Brackets)			
Model	P-Value	R-Squared	C.V.	bo	b1	b2	b3
A	0.0001	0.8559	86.4937	144.866	0.01362		
				[.0001]	[.0001]		
B	0.0001	0.8602	85.1845	138.319	0.01761		
				[.0001]	[.0001]		
C	0.0001	0.8656	83.5298	140.007	0.01681		
				[.0001]	[.0001]		
D	0.0001	0.872	82.2964	64.3617	0.0138	149.6248	
				[.1431]	[.0001]	[.0135]	
E	0.0001	0.9056	71.3503	69.4969	0.0134	55.987	0.018734
				[.0700]	[.0001]	[.3158]	[.0001]
F	0.0001	0.8871	77.2667	-475.45	0.01647	632.3268	
				[.0095]	[.0001]	[.0009]	
G	0.0001	0.8943	75.4981	-385.7	0.15185	492.5689	-0.104759
				[.0359]	[.0418]	[.0127]	[.0685]
H	0.0001	0.89	77.0205	-408.59	0.01678	523.8808	71.359744
				[.0318]	[.0001]	[.0124]	[.2537]
I	0.0001	0.9064	72.7444	-210.49	320.404	0.012931	0.015897
				[.1651]	[.0487]	[.0001]	[.0004]

Models:
A: KSLOC=b0 + b1FP
B: KSLOC=b0 + b1UFP
C: KSLOC=b0 + b1EFP
D: KSLOC=b0 + b1FP + b2Lang
E: KSLOC=b0 + b1FP + b2Lang + b3(FP)Lang
F: KSLOC=b0 + b1UFP + b2VAF
G: KSLOC=b0 + b1UFP + b2VAF + b3(UFP)VAF
H: KSLOC=b0 + b1UFP + b2VAF + b3Lang
I: KSLOC=b0 + b1VAF + b2(UFP)(VAF) + b3(UFP)(Lang)(VAF)

Outlier Analysis (Military Database)

As is readily obvious from the above discussions, every model associated with the investigative questions meets/surpasses all the preestablished criteria except the CV measure where each model did NOT meet the criteria of a CV less than 50. Once again, the Coefficient of Variation (CV) should be less than 50% (50, 59). Coefficient of variation tells you that if you estimated at the center of your data, 2*CV gives you the approximate interval that the prediction may fall at the 95% level of confidence if Y is normally distributed (51). The smaller CV is, the greater the possibility of getting good estimates of the dependent variable at the center of the data. CV is calculated by the square root of the MSE divided by the mean of Y as seen below.

$$CV = S_{yx}/\bar{Y}$$

Since the mean of Y is not changing, it is safe to assume that the variability around the regression line of the actuals (reflected in S_{yx}) is the reason for the CV failing to meet the pre-established criteria. This may be caused by a bad fit of the regression line through the data. However, the R^2 statistics indicate a good fit. The possible cause is that outlier data is adversely affecting the fit of the regression line and resulting statistics.

Outliers with respect to X. The first step in the analysis of outliers for the military database was to examine those observations that were outliers with respect to X. Once again, the rule of thumb used to determine potential outliers was (2*p)/n, where p is the number of parameters including the intercept, and n is the number of observations. If the leverage value was

greater than (2*p)/n (which equals 0.1311 in this case) it was identified as an outlier (51). The CAMS and the SPAS programs in the military database were the only programs that exceeded the leverage value criteria, therefore they were identified as potential outliers. Note that SAS outlier data is found in Appendix C.

Outliers with respect to Y. The military data was examined for outliers with respect to Y. Once again, the studentized residual analysis was used to identify outliers with respect to Y. If the t-value is less than the absolute value of the system studentized residual it is identified as an outlier (51). The t-statistic used was based on an alpha of 0.10 with degrees of freedom equal to 57. The value from the t-tables was approximately 1.674. Five programs, SPAS, CAMS, OLVIMS, CWIMS, and GAFS, had studentized residuals that were greater than the t-value and were identified as potential outliers with respect to Y.

Influential Outliers. Now that the potential outliers with respect to X and Y have been identified, our next step was to determine if these had a significant impact on the model. The three methods that were used to identify the amount of influence of outliers are: the influence of the fitted values (DFFITS), the influence on the regression coefficients (DFBETAS), and Cook's distance test. Once again, the criteria used to determine the influence of an outlier is if the DFFITS absolute value is greater than 1, then the outlier is influential (51). Two systems had DFFITS values greater than 1. The two systems were CAMS and SBSS with DFFITS values of 63.8782 and 1.4844. It can be concluded that these systems had a significant influence on the functional form of the fitted regression line, especially the CAMS program. DFBETAS greater than 1 suggest that the observation has a large influence on

the value of the regression coefficient. The analysis revealed two observations that had a significant influence on the regression coefficients. CAMS had a large impact on the coefficients of external function points (109.688) and the interaction of unadjusted function points and language value, as well as language value by itself. SBSS had a large impact on the coefficient of unadjusted function points (1.927). And, if Cook's D is greater than F_{ratio} for a 0.5 alpha, it is indicative that it is an influential outlier. The F_{ratio} is approximately 0.849. The CAMS was the only system to surpass the 0.849 criteria with a Cook's D of 2204.903.

CAMS has a significant influence on the regression fit. Typically, if a data point is identified as an outlier, it is not deleted unless it is determined that it is not a member population as defined for the research. Being an extreme value is not always enough to justify deleting a data point. To investigate the CAMS system outlier potential, Dub Jones, developer of the SPDS, was called. Jones stated that the CAMS system was similar in terms of functionality to the other systems in the database. It differed only in size because it had to simultaneously handle thousands of users at a number of different sites (43). The added complexity and number of inputs/outputs should be explained within the function point counts and VAF value. CAMS was identified as an outlier in all of the outlier tests to a significant degree. However, it appears that CAMS belongs to the population of MIS/ADP systems. This produces a dilemma in that the CAMS system is clearly much larger than the other systems in the sample, and all of the outlier diagnostics indicate that it is influential in terms of the fit regression line. A decision was made to re-estimate the parameters for all models with the CAMS system deleted from the database. Such an analysis will reveal the nature of

the relationships for smaller MIS/ADP systems. Additionally, with the program differing in magnitude from the rest of the other programs, residual plot analysis (for possible independent transformations), is next to impossible.

To analyze the effectiveness of deleting the CAMS system, another series of SAS runs were performed to ascertain the effects on the regression line via ANOVA table analysis. The measures to be compared to the criteria in Chapter 3 are exhibited in Table 5 below. At first glance, it appears that the outlier deletion has made for a worse fit of the data. Models A through H, testing the IQI questions no longer meet the R^2 criteria of 70%, and the CV shows an even worse predictive capability. While all the models have a significance of 99.9%, a number of the model coefficients have become insignificant. Using the iterative MAXR and COLLINOINT procedure described above, model I in Table 5 shows an improvement over the "best" model in Table 4 prior to the deletion of the outlier. The post-outlier removal "best" model met all the criteria set in Chapter 3 except the CV was 83.6433, still implying a lack of predictive capability. Table 5 also shows that there is no marked difference between the eight models (A-H) addressing the IQIs. It is noted that the induction of Lang (model E) does increase the predictive capability of the model somewhat. The ANOVA tables supporting Table 5 can be found in Appendix E.

An examination of Figure 6 in Chapter 3 will enhance the explanation for the worse fit of the data and deteriorated predictive capability after CAMS was removed. With CAMS included, the statistical values were better because SAS fit a line between a point, CAMS, and a relatively close group of points providing better statistic measures. Without the relatively huge

measures associated with CAMS, the new relative residuals associated with the remainder of the data provide for the worse R^2 and CV values.

Table 5

ANOVA Results of Military Data, CAMS Removed, Straight Linear Regression

Dependent Variable: Ln KSLOC				Coefficients (P-Value in Brackets)			
Model	P-Value	R-Squared	C.V.	bo	b1	b2	b3
A	0.0001	0.64	90.97059	74.32397	0.03631		
				[.0076]	[.0001]		
B	0.0001	0.6399	90.98417	65.182325	0.044129		
				[.0202]	[.0001]		
C	0.0001	0.6428	90.62233	77.766863	0.039314		
				[.0049]	[.0001]		
D	0.0001	0.6547	89.95806	40.533097	0.034759	72.29029	
				[.2521]	[.0001]	[.1462]	
E	0.0001	0.6966	85.16085	-9.399213	0.07029	134.8831	-0.0382
				[.8066]	[.0001]	[.0126]	[.0114]
F	0.0001	0.6506	90.4926	-143.85792	0.040347	224.9578	
				[.3992]	[.0001]	[.2164]	
G	0.0001	0.6604	90.10807	-129.78269	-0.057615	230.3153	0.08043
				[.4458]	[.4851]	[.2042]	[.2364]
H	0.0001	0.6578	90.45341	-98.344593	0.040177	148.9262	54.5603
				[.5764]	[.0001]	[.4474]	[.3118]
I	0.0001	0.7074	83.64332	-12.282559	136.47359	-0.0398	0.0718
				[.7443]	[.0102]	[.0069]	[.0001]

Models:
A: KSLOC=b0 + b1FP
B: KSLOC=b0 + b1UFP
C: KSLOC=b0 + b1EFP
D: KSLOC=b0 + b1FP + b2Lang
E: KSLOC=b0 + b1FP + b2Lang + b3(FP)Lang
F: KSLOC=b0 + b1UFP + b2VAF
G: KSLOC=b0 + b1UFP + b2VAF + b3(UFP)VAF
H: KSLOC=b0 + b1UFP + b2VAF + b3Lang
I: KSLOC=b0 + b1Lang + b2(FP)Lang + b3(UFP)VAF

Transformation Analysis (Military Database)

Because none of the models surpassed the criteria set forth in Chapter 3, the author assumes that the relationship may have been mis-specified. The actual relationship between the IVs and KSLOC may not be linear. Proper specification can be ascertained using prediction plots and residual plot analysis. A prediction plot will show predicted values plotted against the actual values. The prediction plot of each of the SIV model variables will depict the actual relationship between the actual and predicted values. It will show that the slope specified is correct. In this research, it was hypothesized that the function point measures increased as KSLOC increased. This implies a positive first derivative of the regression equation as depicted in Figure 5 in Chapter 3. To ensure a good fit, the actual values should be equally scattered around the prediction line (62:67, 47). A residual plot will plot the residuals (actual values minus the predicted values). A good model will have residuals that are randomly scattered about the line where predicted equals actual values (62:68). If a pattern emerges in the residual plot, it implies that the SIV variable in question should be transformed to provide a better fit (50).

Predication and residual plots for each of the IVs in the entire SPDS database were plotted. These are found in Appendix D, Table 15. The analysis of each of the individual variables is somewhat obscured by the magnitude of the CAMS outlier data point. Since the CAMS was deleted from the data, a clearer view of these relationships will be seen in Appendix D, Table 16. Because CAMS was deleted, patterns in the data are easily seen. The plots in the data still support (+,0) relationships for the variables of FP, UFP, and EFP as advocated by industry experts. The (+,+) relationship of the

VAF variable to KSLOC is definite. The VAF variable will be ANOVA tested using a $y=x^2$ relationship. In a (+,+) relationship, a logarithmic transformation of the both the independent and dependent variables simultaneously, known as "ln-ln" transformations is also recommended (51). The ln-ln transformation will not be used on any IVs except VAF. The residual plot analysis also reveals heteroscedasticity in the data. As the IVs become larger, so do the error variances. To correct for these unequal error variances, the DV of KSLOC will be transformed by taking its natural logarithm (51, 52:146). These models are depicted below in Table 6. VAF Squared, VAF, and the natural log of VAF are each displayed being added to UFP in relation to the natural log of KSLOC. A comparison of models F, G, and H in Table 6 show VAF squared to be the best transformation of the VAF variable. Note that only the "best" transformation of VAF (VAF Squared) are shown in equations used to answer investigative questions in Table 6. The ANOVA tables depicting these transformations are in Appendix E.

The iterative MAXR/COLLINOINT procedure discussed in Chapter 3 was used to develop model K in Table 6. Model K is the "best" model with collinearity mitigated using the model acceptance criteria in Chapter 3. Model K does not include the CAMS data as discussed earlier. The choice of IVs for model K included all the initial IVs as well as the transformations of VAF and its interactions with other variables. The DV, KSLOC, has been transformed to the natural log of KSLOC to correct for the heteroscedasticity seen in the residual plots. Note that the measures of R^2 and CV each get slightly worse in Table 6 after the transformations than prior to the transformations. Additionally, these models do not meet the criteria set in Chapter 3 except for the overall significance level of the model. The variable

Table 6

ANOVA Results of Military Data, CAMS Deleted, VAF & KSLOC Transformed

Dependent Variable: Ln KSLOC				Coefficients (P-Value in Brackets)				
Model	P-Value	R-Squared	Root MSE	b0	b1	b2	b3	b4
A	0.0001	0.3595	1.18832	3.80709	0.00014			
				[.0001]	[.0001]			
B	0.0001	0.3742	1.17461	3.76231	0.00017			
				[.0001]	[.0001]			
C	0.0001	0.3469	1.19987	3.82883	0.00015			
				[.0001]	[.0001]			
D	0.0001	0.4742	1.08713	3.32641	0.00012	1.02833		
				[.0001]	[.0001]	[.0016]		
E	0.0001	0.598	0.96008	2.88898	0.00043	1.57668	-0.00033	
				[.0001]	[.0001]	[.0001]	[.0003]	
F	0.0001	0.513	1.04624	-0.0713	0.0001	4.12556		
				[.9444]	[.0030]	[.0004]		
G	0.0001	0.5199	1.03882	1.78061	9.5E-05	2.24609		
				[.0015]	[.0065]	[.0003]		
H	0.0001	0.5053	1.05447	4.07427	0.00011	3.67924		
				[.0001]	[.0013]	[.0006]		
I	0.0001	0.5402	1.02677	1.6579	0.00048	2.23348	-0.00026	
				[.0029]	[.0714]	[.0002]	[.1439]	
J	0.0001	0.5625	1.00149	1.89528	9.4E-05	1.76343	0.675375	
				[.0005]	[.0055]	[.0045]	[.0319]	
K	0.0001	0.6267	0.91858	2.0794	0.00037	1.07081	-0.0002	1.077551
				[.0001]	[.0005]	[.0013]	[.0043]	[.0524]

Models:

A: LNKSLOC=b0 + b1(FP)

B: LNKSLOC=b0 + b1(UFP)

C: LNKSLOC=b0 + b1(EFP)

D: LNKSLOC=b0 + b1(FP) + b2Lang

E: LNKSLOC=b0 + b1(FP) + b2Lang + b3(FP)Lang

F: LNKSLOC=b0 + b1(UFP) + b2(VAF)

G: LNKSLOC=b0 + b1(UFP) + b2(VAF Squared)

H: LNKSLOC=b0 + b1(UFP) + b2(Ln of VAF)

I: LNKSLOC=b0 + b1UFP + b2(VAF Squared) + b3(UFP)(VAF Squared)

J: LNKSLOC=b0 + b1UFP + b2(VAF Squared) + b3Lang

K: LNKSLOC=b0 + b1UFP + b2(VAF)(Lang) + b3(UFP)(Lang)(VAF Squared) + b4(VAF Squared)

Model K is the "best" available model in this category with collinearity mitigated using the condition number < 10 standard.

coefficient's significance have become less significant as well.

Military Database Investigative Questions Addressed

Investigative Question I (IQI) was How well do function point values predict SLOC for Air Force MIS/ADP projects? IQI will be addressed after answering the subquestions associated with it. The information from Table 6 is used to answer the investigative questions. The first subquestion was Investigative Question Ia (IQIa): How well do adjusted function points predict SLOC in the military environment? Adjusted function points is a very significant predictor of the natural log of KSLOC as demonstrated in model A, Table 6. The model was significant to the 99.9% level. This model does not provide a very good fit of the regression line as demonstrated by a R^2 of 0.3595. This is well below the recommended R^2 value of 0.70. The predictive capability of the adjusted function points is very low as demonstrated by the CV equivalent of Root MSE of 118.83. This is well beyond the recommended CV value of 50.

Investigative Question Ib (IQIb): How well do unadjusted function points predict SLOC in the military environment? The relationship between unadjusted function points and the natural log of KSLOC as demonstrated in model B, Table 6 is significant. The model was significant to the 99.9% level. This model does not provide a very good fit of the regression line as demonstrated by a R^2 of 0.3742. This is well below the recommended R^2 value of 0.70. The predictive capability of the adjusted function points is very low as demonstrated by the CV equivalent of Root MSE of 117.46. This is well beyond the recommended CV value of 50. Note that unadjusted function points has a slightly better goodness of fit and predictive capability than adjusted function points.

Investigative Question Ic (IQIc): How well do external function points predict SLOC in the military environment? The relationship between external function points and the natural log of KSLOC is very significant as demonstrated in model B, Table 6. The model was significant to the 99.9% level. This model does not provide a very good fit of the regression line as demonstrated by a R^2 of 0.3469. This is well below the recommended R^2 value of 0.70. The predictive capability of the adjusted function points is very low as demonstrated by the CV equivalent of Root MSE of 119.99. This is well beyond the recommended CV value of 50. Note that external function points has a slightly worse goodness of fit and predictive capability than the other function point measures.

Investigative Question Id (IQId): To what degree is the relationship between function points and SLOC affected by language? This question is addressed by models D and E in Table 6. The inclusion of the Lang variable in the model significantly enhances the model. By adding only Lang to the model, the R^2 and Root MSE improved significantly over the function point only model. In model D, the coefficient of Lang was significant to the 99.84% level. In model E, the coefficient of the Lang term was significant to the 99.99% level, and the coefficient of the interaction of function points and Lang was significant to the 99.97% level. This demonstrates that the segregation of function point measures by language is significant and enhances function point's predictive capability. However, note that the Lang models do not meet the criteria for the R^2 or Root MSE established in Chapter 3.

Investigative Question Ie (IQIe): To what degree is the relationship between function points and SLOC affected by program complexity? This

question is addressed by models F, G, H, and I in Table 6. Models F, G, and H are used to select the best transformation of VAF. As was the case with Lang, the inclusion of a VAF-related variable in the model significantly enhances the model. By adding a VAF-related variable to the model, the R^2 and Root MSE improved significantly over the function point only model. The best VAF-related variable selected was VAF squared due to its R^2 and Root MSE values. In model G, the coefficient of VAF squared was significant to the 99.97% level. In model I, the coefficient of the VAF squared term was significant to the 99.98% level, and the coefficient of the interaction of unadjusted function points and VAF squared was significant to the 85.61% level. This demonstrates that complexity in programs, measured by VAF squared, is significant and enhances function point's predictive capability. However, note that the VAF squared models do not meet the criteria for the R^2 or Root MSE established in Chapter 3.

Investigative Question If (IQIf): To what degree is the relationship between function points and SLOC affected by program complexity and program language? This question is addressed by model J in Table 6. The combination of VAF squared and Lang in a single equation definitely provides for a better model than an unadjusted function point model as would be expected. Additionally, it provides for a better fit and predictive capability than the previous models except for model E. This could imply that more of the error of the estimates is explained by the Lang variable than the VAF squared variable. The measures of R^2 and CV do not differ enough to support this contention though.

Investigative Question Ig (IQIg): Using all the available independent variables and interactions between these variables, what is the best

predictive model of SLOC in the military environment? This question is addressed by model K in Table 6. Once again, this was the "best" model from the SPDS database after the outlier (CAMS) was removed, appropriate IVs and KSLOC were transformed after residual plot analysis, and the iterative MAXR/COLLINOINT procedure was implemented to mitigate collinearity. The model is exhibited below in equation (18).

$$
\begin{aligned}
LNKSLOC = 2.0794 &+ 0.0004(UFP) + 1.0708(VAF)(Lang) \\
&+ (-0.0002)(UFP)(Lang)(VAF\ Squared) \\
&+ 1.0776(VAF\ Squared)
\end{aligned}
\tag{19}
$$

where UFP is Unadjusted Function Points

LNKSLOC is the natural logarithm of KSLOC

Lang is the language indicator variable

Note that this model does not meet the acceptance criteria set in Chapter 3. Each of the coefficients are statistically significant from the 94.76% to the 99.99% level. The model itself is statistically significant to the 99.99% level. The model's goodness of fit falls short of the criteria. The model only has an R^2 of 62.67%. The predictive capability of the model is also lacking. With a CV criteria of less than 50%, the model exhibits a Root MSE (CV equivalent measure under the logarithmic transformation of the DV) of 91.86%. As an additional note, this model is to be used for programs of roughly the same function point count as those in the cluster of data points in the SPDS database after the deletion of the CAMS program. The relevant range for future function point counts using this data will be 0 to 40,372 function

points. The 40,372 function point count is derived from the largest program in the SPDS after the deletion of CAMS.

Outside of this relevant range, the ability to estimate SLOC is even more tenuous because estimates would only be based on a regression line fitted to the cluster of data and the CAMS data point. However, with the limited data, an estimate based on minimal data is preferred to one based on no data. The basis for an estimate outside the relevant range is found in model I in Table 4. This is the "best" model for the entire SPDS database and is displayed below.

$$\begin{aligned} KSLOC = -210.49 &+ 320.40(VAF) + 0.0129(UFP)(VAF) \\ &+ 0.0159(UFP)(Lang)(VAF) \end{aligned}$$

where UFP is Unadjusted Function Points

Lang is the language indicator variable

When this model was suggested, it was prior to the residual plot analysis step. Since this model is based essentially on a regression line between the cluster of data and the CAMS data point, two points in essence, assessing the residual plots for transformations of the IVs would be inappropriate. However, the residual plot of this "best" equation's predicted values versus the actual SLOC values will provide information on the variance of error terms. The predicted values of the regression model are represented by the term "pred". The residual plot is found in Appendix D, Table 17. Note that the residual plot only depicts residuals in the relevant range since inclusion of the CAMS residual would occlude detailed analysis of the residual plot due to its magnitude.

The residual plot reveals the existence of heteroscedasticity in the data. As mentioned previously, transforming the DV by taking its natural logarithm will mitigate the effects of heteroscedasticity (51). The new equation is exhibited below:

$$LNKSLOC = -0.1056 + 4.279(VAF) + 9.950*10^{-6}(UFP)(VAF) + 2.468*10^{-5}(UFP)(Lang)(VAF) \quad (20)$$

Where LNKSLOC is the natural logarithm of KSLOC

UFP is Unadjusted Function Points

Lang is the language indicator variable

Equation (20) represents the regression equation for function point values outside the cluster of data points in the range of 40,372 to 297,313 function points. The statistics that describe this model are in Appendix E, Table 22. This model is significant to the 99.99% level. Each of the non-y-intercept coefficients are significant to the 98.1% level or higher. However, the model does have a low predictive capability and substandard goodness of fit. The model's R^2 was 55.84%, well below the R^2 acceptance criteria in Chapter 3. With a CV criteria of less than 50%, the model exhibits a Root MSE (CV equivalent measure under the logarithmic transformation of the DV) of 104.6%.

The answered IQI subquestions are the foundation for answering the Investigative Question I (IQI) of how well do function point values predict SLOC for Air Force MIS/ADP projects? Based on the SPDS database information, a significant relationship exists between function points and SLOC. In fact, all of the function point related values, including unadjusted function points, external function points, VAF, and the language indicator

variable, were highly significant. However, none of the models provided a goodness of fit that met the criteria set in Chapter 3. Additionally, the predictive capability of the models is lacking. The CV criteria measure of less than or equal to 50 was nearly doubled. Therefore, expect high variability in SLOC predictions when using these military models. Note that unadjusted function points provides a better model than function points or external function points. In fact, unadjusted function points appears twice in the "best" model, model K in Table 6, whereas function points and external function points do not appear at all. In conclusion, models based on the SPDS data do not provide good predictions for SLOC. If the models depicted in equations (18) or (19) are used, they should be used with caution and used only in the relevant ranges of function points previously discussed.

Initial Results (Commercial Database)

The same general steps will be used to analyze the data in the commercial database as used for the military database. The ANOVA information to answer the IQII investigative questions is exhibited in Table 7 below. As in the military data, all of the models representing each of the investigative questions were found to have a 99.9% level of significance as seen in the first column. Also, note that in each model, except model A, the R^2 values surpasses the 0.70 criteria. In addition, each of the coefficient's t-test significance levels for the function point oriented measures are represented by p-values in brackets. The all of them are significant at the 99.9% level of significance. The coefficients for Lang, the language indicator variable, in the various models appear significant except where the equation contains another variable with Lang in it. This is attributed to collinearity

Table 7

ANOVA Results of Commercial Data, All Programs Included

Dependent Variable: KSLOC				Coefficients (P-Value in Brackets)			
Model	P-Value	R-Squared	C.V.	Bo	B1	B2	B3
A	0.0001	0.6521	62.74605	-22.6198	0.168594		
				[.2483]	[.0001]		
B	0.0001	0.7111	57.17882	-30.3988	0.180566		
				[.0950]	[.0001]		
C	0.0001	0.714	57.6754	-6.93042	0.166857	-69.8577	
				[.7116]	[.0001]	[.0083]	
D	0.0001	0.7403	55.73963	-16.1114	0.178449	13.29625	-0.1106
				[.3928]	[.0001]	[.7933]	[.0681]
E	0.0001	0.7148	57.59059	27.29712	0.181938	-58.548	
				[.7522]	[.0001]	[.4961]	
F	0.0001	0.7464	55.07422	-239.775	0.612086	209.9718	-0.4281
				[.1234]	[.0055]	[.1763]	[.0440]
G	0.0001	0.7566	53.95971	-20.3715	0.1777	5.122305	-60.4898
				[.8069]	[.0001]	[.9517]	[.0194]
H	0.0001	0.7746	51.93001	-23.6614	0.183943	3.548406	-0.09041
				[.7667]	[.0001]	[.9646]	[.0044]

Models:

A: KSLOC=b0 + b1(FP)

B: KSLOC=b0 + b1(UFP)

C: KSLOC=b0 + b1(FP) + b2(Lang)

D: KSLOC=b0 + b1(FP) + b2Lang + b3(FP)Lang

E: KSLOC=b0 + b1(UFP) + b2VAF

F: KSLOC=b0 + b1(UFP) + b2(VAF) + b3(UFP)VAF

G: KSLOC=b0 + b1(UFP) + b2(VAF) + b3Lang

H: KSLOC=b0 + b1(UFP) + b2(VAF) + b3(UFP)Lang

Model H is the "best" available model in this category with collinearity mitigated using the condition number < 10 standard.

between Lang and the interactive variable. This is not the case for the complexity rating of VAF. VAF appears highly insignificant by itself as a variable except when combined with another variable. The CV values for each of these models is better than the best model in all the military database ANOVA tables. Therefore, even the worst model in this table provides better predictive capabilities than the best model in the military

database. Another point is that the UFP based model proved to be a better model of KSLOC than FP. The information needed to derive the EFP measure was not available for this database. The same MAXR/COLLINOINT procedure used for the military data was used to obtain the "best" model for the commercial database. This "best" model, model H, comes very close to meeting the criteria set in Chapter 3. The coefficient for VAF is statistically insignificant and the CV is just over the criteria threshold of 50 with a CV of 51.93. Model H also includes UFP instead of FP. This information shows that unadjusted function points are a good measure for SLOC but the variability in the data cause doubt as to its predictive capability in the commercial environment as well. As before, the supporting ANOVA tables will be found in Appendix E.

Outlier Analysis (Commercial Database)

As is readily obvious from the above discussions, every model associated with the investigative questions meets/surpasses the all the preestablished criteria except the CV measure (and significance of the VAF oriented coefficients) where each model did NOT meet the criteria of a CV less than 50. Once again, the Coefficient of Variation (CV) should be less than 50% (50, 59). The same procedure to check for outliers will be used on the commercial database as was used on the military database to check for outliers. The data used for outlier analysis is found in Appendix C, Table 14.

Outliers with respect to X. The first step in the analysis of outliers was to examine those observations that were outliers with respect to X. The rule of thumb used to determine potential outliers was, if the leverage value was greater than (2*p)/n (which equals 0.205 in this case), it was identified as an

outlier (51). The observation #14 and the observation #29 programs in the commercial database were the only programs that exceeded the leverage value criteria. Therefore they were identified as potential outliers with respect to X.

Outliers with respect to Y. To identify outliers with respect to Y the studentized residual analysis was used. If the t-value is less than the absolute value of the system studentized residual it is identified as an outlier (51). The value from the t-tables was approximately 1.691 based on an alpha of 0.10 with degrees of freedom equal to 35. Two programs, observations #1 and #30 had studentized residuals that were greater than the t-value and were identified as potential outliers with respect to Y.

Influential Outliers. The three methods used to identify the amount of influence of outliers are: the influence of the fitted values (DFFITS), the influence on the regression coefficients (DFBETAS), and Cook's distance test. The criteria used to determine the influence of an outlier is if the DFFITS absolute value is greater than 1, then the outlier is influential (51). Two systems had DFFITS values greater than 1. The two systems were #1 and #30 with DFFITS values of 1.4102 and 1.6647. Another criteria used to determine the influence is if systems with DFBETAS greater than one were considered potentially influential. The analysis revealed two observations that had a significant influence on the regression coefficients of unadjusted function points. #1 had a DFBETA of 1.2165 as did #30 with a DFBETA of 1.1919. Finally, if Cook's D is greater than F_{ratio} for a 0.5 alpha, it is indicative that it is an influential outlier. The F_{ratio} is approximately 0.849. None of the systems surpass the Cook's D criteria.

None of the systems had a significant influence on the regression fit consistently on all of influence criteria. The author is subjectively assessing that the extent of the influence present is not large enough to warrant deleting any observation.

Transformation Analysis (Commercial Database)

A similar procedure as was performed on the military data will be used here to ascertain if any of the variables need to be transformed. If a pattern emerges in the residual plot, it implies that the SIV variable in question should be transformed to provide a better fit (50). Predication and residual plots of the entire commercial database were plotted. These are found in Table 18 in Appendix D. The two function point measures did not appear to form any pattern. The VAF plots did show a definite (+,+) relationship. The VAF variable will be transformed using a $y=x^2$ relationship as well as in logarithmic transformations of the both the independent and dependent variables simultaneously, known as "ln-ln" transformations. Also, the logarithmic transformation of the DV is justified because the residual plots of function points, unadjusted function points, and VAF show definite heteroscedastic tendencies. The result of these transformations appear in Table 8 below. Note that VAF squared appeared in model F as a better variable than the Ln of VAF or VAF alone. Model J is the model, for the commercial database, obtained from the MAXR/COLLINOINT procedure as being the "best" possible model in the table with collinearity mitigated using the condition number less than 10 standard.

Commercial Database Investigative Questions Addressed

Investigative Question II (IQII) was "Does the strength of the prediction relationship between function points and SLOC differ for Air Force

Table 8

ANOVA Results of Commercial Data, VAF & KSLOC Transformed

Dependent Variable: LNKSLOC							
				Coefficients (P-Value in Brackets)			
Model	P-Value	R-Squared	Root MSE	bo	b1	b2	b3
A	0.0001	0.6117	0.66409	3.02872	0.001496		
				[.0001]	[.0001]		
B	0.0001	0.6245	0.65299	2.999831	0.00155		
				[.0001]	[.0001]		
C	0.0001	0.697	0.59473	3.19743	0.001477	-0.751191	
				[.0001]	[.0001]	[.0030]	
D	0.0001	0.7037	0.59639	3.24008	0.001423	-1.137485	0.000514
				[.0001]	[.0001]	[.0270]	[.3775]
E	0.0001	0.6247	0.66187	3.101147	0.001553	-0.102812	
				[.0015]	[.0001]	[.9092]	
F	0.0001	0.625	0.66155	3.098582	0.001554	-0.099679	
				[.0001]	[.0001]	[.8272]	
G	0.0001	0.6245	0.66199	2.99653	0.00155	-0.007033	
				[.0001]	[.0001]	[.9936]	
H	0.0001	0.6272	0.66904	3.426312	0.001041	-0.427803	0.000504
				[.0005]	[.3792]	[.6251]	[.6589]
I	0.0001	0.6961	0.60401	2.883376	0.001497	0.30001	-0.725319
				[.0001]	[.0001]	[.4967]	[.0071]
J	0.0001	0.7141	0.58588	3.251622	0.001417	-1.122414	0.000516
				[.0001]	[.0001]	[.0128]	[.2910]

Models:
A: LNKSLOC=b0 + b1FP
B: LNKSLOC=b0 + b1UFP
C: LNKSLOC=b0 + b1FP + b2Lang
D: LNKSLOC=b0 + b1FP + b2Lang + b3(FP)(Lang)
E: LNKSLOC=b0 + b1UFP + b2VAF
F: LNKSLOC=b0 + b1UFP + b2(VAF Squared)
G: LNKSLOC=b0 + b1UFP + b2(Ln of VAF)
H: LNKSLOC=b0 + b1UFP + b2(VAF Squared) + b3(UFP)(VAF Squared)
I: LNKSLOC=b0 + b1UFP + b2(VAF Squared) + b3Lang
J: LNKSLOC=b0 + b1FP + b2(VAF)(Lang) + b3(UFP)(Lang)(VAF Squared)

Model G is the "best" available model in this category with collinearity mitigated using the condition number < 10 standard.

and non-Air Force projects?" IQII will be addressed after answering the associated subquestions using information from Table 8. The first subquestion was Investigative Question IIa (IQIIa): How well do adjusted function points predict SLOC in the commercial environment? Adjusted function points is a very significant predictor of the natural log of KSLOC as demonstrated in model A, Table 8. The model was significant to the 99.9% level. This model does not provide the goodness of fit of the regression line specified in the selection criteria. The R^2 of 0.6117 is well below the recommended R^2 value of 0.70. The predictive capability of the adjusted function points is low as demonstrated by the CV equivalent of Root MSE of 66.409. This is well beyond the recommended CV value of 50.

Investigative Question IIb (IQIIb): How well do unadjusted function points predict SLOC in the commercial environment? Unadjusted function points is a very significant predictor of the natural logarithm of KSLOC as demonstrated in model B, Table 8. The model was significant to the 99.9% level. This model does not provide a good fit of the regression line as demonstrated by a R^2 of 0.6245, well below the recommended R^2 value of 0.70. The predictive capability of the unadjusted function points is very low as demonstrated by the CV equivalent of Root MSE of 65.299. This is does not meet the recommended CV value of 50. Note that unadjusted function points has a slightly better goodness of fit and predictive capability than adjusted function points.

Investigative Question IIc (IQIIc): To what degree is the relationship between function points and SLOC affected by language? This question is addressed by models C and D in Table 8. The inclusion of the Lang variable

in the model significantly enhances the model. By adding only Lang to the model, the R^2 and Root MSE improved significantly over the function point only model. In model C, the coefficient of Lang was significant to the 99.7% level. In model D, the coefficient of the Lang term was significant to the 97.3% level, and the coefficient of the interaction of function points and Lang was insignificant. It was probably insignificant due to collinearity with the Lang term. The significant Lang variables demonstrate that the segregation of function point measures by language is significant and enhances function point's predictive capability in the commercial environment. However, note that the Lang models do not meet the criteria for the R^2 or Root MSE established in Chapter 3.

Investigative Question IId (IQIId): To what degree is the relationship between function points and SLOC affected by complexity? This question is addressed by models E, F, G, and H in Table 8. Models E, F, and G are used to select the best transformation of VAF. By adding a VAF-related variable to the model, the R^2 did not change significantly and Root MSE marginally degraded over the unadjusted function point only model. The best VAF-related variable selected was VAF squared due to its R^2 and Root MSE values. In model F, the coefficient of VAF squared was insignificant. In model H, the coefficient of the VAF squared term was insignificant, as was the coefficient of the interaction of unadjusted function points and VAF squared. These models demonstrate that complexity in programs, measured by VAF squared, is insignificant and do not enhance function point's predictive capability. As would be suspected, note that the VAF squared models do not meet the criteria for the R^2 or Root MSE established in Chapter 3.

Investigative Question IIe (IQIIe): To what degree is the relationship between function points and SLOC affected by program complexity and program language in the commercial environment? This question is addressed by model I in Table 8. The combination of VAF squared and Lang in a single equation provides for a minimally better model than an unadjusted function point model as would be expected. Additionally, it provides for a better fit and predictive capability than the previous models except for model D. This could imply that more of the error of the estimates is explained by the Lang variable than the VAF squared variable. The measures of R^2 and CV do not differ enough to support this contention though.

Investigative Question IIf (IQIIf): Using all the available independent variables and interactions between these variables, what commercial model provides the best statistical attributes devoid of collinearity? This question is addressed by model J in Table 8. Once again, this was the "best" model from the SPDS database after the outlier (CAMS) was removed, appropriate IVs and KSLOC were transformed after residual plot analysis, and the iterative MAXR/COLLINOINT procedure was implemented to mitigate collinearity. The model is exhibited below in equation (21).

$$LNKSLOC=b0 + b1FP + b2(VAF)(Lang) + b3(UFP)(Lang)(VAF\ Squared) \quad (21)$$

where FP is Adjusted Function Points

LNKSLOC is the natural logarithm of KSLOC

Lang is the language indicator variable

Note that this model does not meet the acceptance criteria set in Chapter 3. Each of the coefficients are statistically significant from the 70.9% to the 99.99% level. The model itself is statistically significant to the 99.99% level. The model's goodness of fit narrowly surpasses the criteria. The model only has an R^2 of 71.41%. The predictive capability of the model is lacking. With a CV criteria of less than 50, the model exhibits a Root MSE (CV equivalent measure under the logarithmic transformation of the DV) of 58.588. The relevant range for future function point counts using this data will be 0 to 2,307 function points. The 2,307 function point count is obtained from the largest program in the commercial database.

The answered IQI subquestions are the foundation for answering the Investigative Question II (IQII), "Does the strength of the prediction relationship between function points and SLOC differ for Air Force and non-Air Force projects?" The commercial database information exhibited a significant relationship exists between function points and SLOC as was the case in the SPDS data. Unlike the SPDS data, all of the function point related values, including unadjusted function points, VAF, and the language indicator variable, were not significant. All the VAF term coefficients in the commercial database were insignificant. While none of the SPDS models provided a goodness of fit that met the criteria set in Chapter 3, only the "best" commercial model (model J) marginally surpassed the R^2 criteria of 70%. Therefore, both database's models do not measure the total variability in the dependent random variable explained by the regression line very well. Additionally, the predictive capability of all of the models is lacking. Neither the SPDS nor the commercial database models met the CV criteria measure of less than or equal to 50. Therefore, expect high variability in

SLOC predictions when using the commercial and military models, especially with the military based models. Also, note that unadjusted function points provided a better model than function points in both cases. In the military models, unadjusted function points appears twice in the "best" model, model K in Table 6, whereas function points and external function points do not appear at all. Comparatively, in the commercial "best" model, function points and unadjusted function point measures were selected. In conclusion, as was the case with the SPDS models, models based on the commercial data do not provide good predictions for SLOC. If the SPDS or commercial models depicted in equations (19), (20), or (21) are used, they should be used with caution and used only in the relevant ranges of function points previously discussed.

Function Point to SLOC Conversion

Investigative Question III (IQIII) asked "How well do function point-to-SLOC conversion tables created from Air Force and commercial data compare to function point-to-SLOC conversion tables provided by industry experts?" This section summarizes how well function point-to-SLOC information within the SPDS database (military database) and the commercial database compare to function point-to-SLOC conversion tables provided by industry experts. Table 9 summarizes the supporting information. To address this question for the military database, regression using the 26 COBOL only programs from the military database was applied to test the relationship between function points and COBOL SLOC. The test is limited to only the COBOL programs because that is the only single language

Table 9

Function Point to SLOC Conversion Comparisons (Military & Commercial Databases)

MILITARY DATA:

				Coefficients (P-Value in Brackets)			
Model	P-Value	R-Squared	C.V.	Bo	B1	B2	B3
A	0.0001	0.872	82.29642	64.361749	0.013804	149.62475	
				[.1431]	[.0001]	[.0135]	
B	0.0001	0.9056	71.35031	69.496854	0.013403	55.987004	0.018734
				[.0700]	[.0001]	[.3158]	[.0001]
C	0.0001	0.9631	64.59484	69497	13.402644		
				[.0359]	[.0001]		
D	0.0001	0.9594	69.49692	13.663468			
				[.0001]			

Models:
A: KSLOC=b0 + b1FP + b2Lang
B: KSLOC=b0 + b1FP + b2Lang + b3(FP)Lang
C: SLOC=b0 + b1(FP)
D: SLOC=b0(FP)
NOTE: Models C & D are limited to the COBOL only programs. Model D has no intercept in the equation.

COMMERCIAL DATA:

				Coefficients (P-Value in Brackets)			
Model	P-Value	R-Squared	C.V.	Bo	B1	B2	B3
E	0.0001	0.714	57.6754	-6.930423	0.166857	-69.85771	
				[.7116]	[.0001]	[.0083]	
F	0.0001	0.7403	55.73963	-16.1114	0.178449	13.296245	-0.110602
				[.3928]	[.0001]	[.7933]	[.0681]
G	0.0001	0.7174	53.23012	-16111	178.4488		
				[.4553]	[.0001]		
H	0.0001	0.8603	52.89721	165.13743			
				[.0001]			

Models:
E: KSLOC=b0 + b1FP + b2Lang
F: KSLOC=b0 + b1FP + b2Lang + b3(FP)Lang
G: SLOC=b0 + b1(FP)
H: SLOC=b0(FP)
NOTE: Models G & H are limited to the COBOL only programs. Model H has no intercept in the equation.

with enough programs, 26, to be considered a statistically valid sample. Models of the relationship between function points and SLOC will allow for a

regression-based y-intercept as well as a y-intercept set to zero. The function point-to-SLOC conversion tables reflect a linear relationship in which the Y-intercept is set to zero. By including the regression with the y-intercept, a comparison to the forced y-intercept of zero is possible. The statistics will validate the merit of the SLOC to function point conversion tables, at least for the COBOL. A similar analysis was used to test the 31 COBOL programs in the commercial database. Additionally, an analysis of the answers to investigative questions IQId and IQIIc will be included. These are the questions that determine the degree of the relationship between function points and SLOC is affected by language. While the data is limited, there is an adequate number of COBOL programs to make an assessment of that portion of the conversion tables.

For the military database with CAMS included, models A and B are provided to show that Lang is a significant factor. In model A, the coefficient of Lang is significant to the 98.65% level. As a reminder, Lang is the variable that measures the significance in the difference between COBOL only programs and the remaining programs. Testing was limited to programs written only in COBOL because that is the only single language with enough samples to be considered valid. Models C and D depict ANOVA table values for these 26 military COBOL programs. Note in model C that the y-intercept is large in magnitude and is significant. Model C is also a better model based on R^2, CV, and F-test criteria than model D, implying that the linear relationship with a zero y-intercept hypothesized may not be appropriate. Since the SLOC to function point conversion table concept implies a direct linear relationship between the two, the y-intercept is zero. Model D, via SAS, has forced the y-intercept to zero in order to test this hypothesis.

Model D has a significance level of 99.9% and a R^2 of 0.9594. However, its poor predictive capability is reflected in the CV of 69.49692. Therefore, it appears that the model and its goodness of fit are very significant, but its predictive capability is lacking. The coefficient of function points is 13.663. This yields a 13.663 COBOL SLOC/function point conversion factor. This differs significantly from the 100 COBOL SLOC/FP suggested by Reifer (61:164) and the 105 COBOL SLOC/FP suggested by Jones (33:98, 34:76). It can be concluded that based on the data from the SPDS database, the industry standard SLOC/FP conversion factors should not be used on military ADP programs.

For the commercial database, models E and F are provided to show that Lang is a significant factor. In model E, the coefficient of Lang is significant to the 99.17% level. In the commercial database there are 31 COBOL only programs. Once again, testing was limited to the COBOL only programs because COBOL is the only single language with enough samples to be considered valid for the commercial database as well. Models G and H depict ANOVA table values for these 31 commercial COBOL programs. Model H forced the y-intercept to zero in order to address the investigative question. Model H has a significance level of 99.9% and a R^2 of 86.03%. However, its predictive capability is reflected in the CV of 52.89721. Note in model G that the y-intercept is large in magnitude but insignificant, supporting the notion that the 0-intercept model is appropriate. Therefore, it appears that the model and its goodness of fit are very significant, but its predictive capability is slightly worse that the criteria set in Chapter 3. The coefficient of function points is 165.14. This yields a 165.14 COBOL SLOC/function point conversion factor. As in the military database, this

differs significantly from the 100 COBOL SLOC/FP suggested by Reifer (61:164) and the 105 COBOL SLOC/FP suggested by Jones (33:98, 34:76). A possible reason for such a vast difference is that the programs in the commercial database were being developed when function points was a new concept and standardized counting methodologies were hadn't been developed yet. It can be concluded that based on the data from the commercial database, the industry standard SLOC/FP conversion factors are not supported based on data from older, commercial ADP programs. With such a large range (13 t0 165) for COBOL SLOC to function points between these two databases, conversion factors as useful SLOC estimating tools are tenuous at best. Additionally, conversion factors should only be used on programs that are very similar (same development group or company, same timeframe, same type of application) to the database from which they were developed.

V. *Summary and Recommendations*

Introduction

Chapter 5 summarizes the results of the research based on iterations of modeling the relationships between various function point-related independent variables and the number of SLOC on a software project. The summary discusses these relationships in the military and commercial environment. The recommendations for use of the models and for future study are also provided.

Summary

The major objective of this research was to determine how well function point values predict SLOC for MIS/ADP projects. Based on the use of a database of programs developed by the military and a database of programs developed commercially, a comparison between the function point to SLOC predictive capabilities was performed. The methodology for this comparison was divided into two parts. First, for each development environment, the various function point measures and their derivatives were incorporated into models to ascertain these measure's predictive capability, significance level, and measure of fit of the predicted regression line. Second, for each of the two environments, the "best" possible model was developed having the most predictive capability, having the highest significance, and providing the best measure of fit of the predicted SLOC values to the SLOC values. Finally, some industry experts have supported the use of function point to SLOC conversion tables. The concept was tested using the limited data available in the two databases for each environment.

Military Models

Using information from the military environment, each of the various function point measures and their derivatives were assessed using modeling techniques. Outlier analysis revealed the need to delete one observation, the CAMS program from the SPDS database. Analysis of prediction and residual plots revealed the need to transform the VAF variable and the dependent variable of KSLOC. After assessing the various transformations of the independent variables, dependent variables, and deletions of the possible outlier observations, it was demonstrated that the unadjusted function point measure by itself to be a better predictor of SLOC than the function point measure. Unadjusted function points is the function point count prior to being multiplied by the VAF. External function points, function point measures based solely on external inputs/outputs to an application boundary, proved to be the worst predictor of SLOC of the three function point measures. Note that none of the function point measure models fulfilled the criteria of a 70% significance level, a 70% R^2, and a coefficient of variation less than 50%.

In the military environment, the significance of the independent variables, the Lang variable and the Value Adjustment Factor (VAF) were also assessed. The Lang variable measured the significance of the the COBOL only programs ability in the military data in the database to aid in predicting SLOC versus the other programs with mixtures of languages and other languages. Lang was extremely significant, implying a significant difference between function point counts in differing languages. VAF, the variable measuring complexity, was an extremely significant contributor to SLOC estimations. VAF's significance supported the need to account for differing

levels of program complexity. Residual plot analysis had identified that the variable VAF increases at an increasing rate in relation to SLOC. Combining the VAF term and Lang variables simultaneously only added marginal improvements over models with these terms included singularly.

Using all the available independent variables and interactions between these variables, a military model providing the best statistical attributes devoid of collinearity was developed. The model is exhibited below.

$$\begin{aligned} LNKSLOC = 2.0794 &+ 0.0004(UFP) + 1.0708(VAF)(Lang) \\ &+ (-0.0002)(UFP)(Lang)(VAF\ Squared) \\ &+ 1.0776(VAF\ Squared) \end{aligned}$$

where UFP is Unadjusted Function Points

LNKSLOC is the natural logarithm of KSLOC

Lang is the language indicator variable

The model itself is statistically significant to the 99.99% level, has an R^2 of 62.67%, and a Root MSE (CV equivalent measure under the logarithmic transformation of the DV) of 91.86%. For usage, the relevant range for future function point counts using this data will be 0 to 40,372 function points. For programs outside this relevant range, a regression line was fitted to the cluster of data and the deleted influential outlier. Although a very tenuous model, the model is displayed below.

$$\begin{aligned} LNKSLOC = -0.1056 &+ 4.279(VAF) + 9.950 \times 10^{-6}(UFP)(VAF) \\ &+ 2.468 \times 10^{-5}(UFP)(Lang)(VAF) \end{aligned}$$

Where LNKSLOC is the natural logarithm of KSLOC

UFP is Unadjusted Function Points

Lang is the language indicator variable

This equation represents the regression equation for function point values in the range of 40,372 to 297,313 function points. This model is significant to the 99.99% level, has an R^2 of 55.84%, and a Root MSE (CV equivalent measure under the logarithmic transformation of the DV) of 104.6%.

Although a significant relationship exists between function points and SLOC, none of the military models provided a goodness of fit, predictive capability, and significance level simultaneously to make it an acceptable model. Therefore, expect high variability in SLOC predictions when using these military models. If either of the military models depicted above are used, they should be used with caution and used only in the relevant ranges of function points mentioned.

Commercial Models

Using information from the commercial environment, each of the various function point measures and their derivatives were assessed using modeling techniques. Outlier analysis revealed that no observations were influential enough to be deleted. As with the military data, analysis of prediction and residual plots revealed the need to transform the VAF variable and the dependent variable of KSLOC. After assessing the various transformations of the independent variables, dependent variables, and deletions of the possible outlier observations, it was demonstrated that the unadjusted function point measure by itself to be a better predictor of SLOC than the function point measure.

In the commercial environment, the significance of the independent variables, the Lang variable and the Value Adjustment Factor (VAF) were also assessed. The Lang variable measured the significance of the the COBOL only programs ability in the commercial data in the database to aid in predicting SLOC versus the other programs with mixtures of languages and other single languages. Lang was extremely significant, implying a significant difference between function point counts in differing languages. Differing from the military data, VAF and its possible tranforms were an insignificant contributor to SLOC estimations. Residual plot analysis had identified that the VAF variable increases at an increasing rate in relation to SLOC. The combination of VAF squared and Lang in a single equation provided for a minimally better model than an unadjusted function point model as would be expected.

Using all the available independent variables and interactions between these variables, a commercial model providing the best statistical attributes devoid of collinearity was developed. The model is exhibited below.

LNKSLOC=b0 + b1FP + b2(VAF)(Lang) + b3(UFP)(Lang)(VAF Squared)

where FP is Adjusted Function Points

LNKSLOC is the natural logarithm of KSLOC

Lang is the language indicator variable

The model itself is statistically significant to the 99.99% level, has an R^2 of 71.41%, and a Root MSE (CV equivalent measure under the logarithmic transformation of the DV) of 58.588%. For usage, the relevant range for

future function point counts using this data will be 0 to 2,307 function points. Each of the coefficients are statistically significant from the 70.9% to the 99.99% level.

Although a significant relationship exists between function points and SLOC in the commercial environment, none of the commercial models provided a goodness of fit, predictive capability, and significance level simultaneously to make it an acceptable model. Note that the models derived from the commercial data were consistently better models than those derived from the military data. However, expect high variability in SLOC predictions when using these commercial models. As with the military models, the "best" commercial model should be used with caution and used only in the relevant range of function points mentioned.

SLOC to Function Point Conversion Factors

The research shows that there is some validity to the concept of creating function point to SLOC conversion tables. However, it does not necessarily support the function point to SLOC conversion tables provided by industry experts. The military database, using solely the COBOL only programs and an ANOVA with the intercept set to zero as would be the case in a function point to conversion table. The relationship yielded a 99.9% significance level, an R^2 of 95.94%, and a CV of 69.5. This function point conversion relationship was highly significant and provided a good fit of the data. However, it did have a lot of variability in its predictive capability though. Industry experts submit that the number of COBOL SLOCs to function points are 100 COBOL SLOC/function point (61:164) or 105 COBOL

SLOCs/function point (34:105). The military data yielded a 13.66 COBOL SLOC/function point conversion factor.

As with the military data, the commercial data research also shows that there is some validity to the concept of creating function point to SLOC conversion tables. However, it did not necessarily support the function point to SLOC conversion tables provided by industry experts. The COBOL only programs in the commercial database yielded a 99.9% significance level, an R^2 of 86.03%, and a CV of 52.89. This function point conversion relationship was highly significant and provided a good fit of the data. It did have some variability in its predictive capability though. Once again, industry experts submit that the number of COBOL SLOCs to function points are 100 COBOL SLOC/function point (61:164) or 105 COBOL SLOCs/function point (34:105). The commercial data yielded a 165.14 COBOL SLOC/function point conversion factor.

Recommendations for Use

There is definitely a relationship between the various function point measures and KSLOC. The "best" models for the commercial and military databases are only recommended for future use on other programs that are similar to the programs in the database used to build the model. By looking at the differences in the "best" models from each of the two environments, the need to use models developed in similar environments is made clear. The "best" models for each environment contain much variability from the actual KSLOC values. This variability in the military data may have come from different SLOC counting methodologies used or the different levels of training that individual function point counters had received at the Standard

Systems Center. The variability in the commercial models may be attributed to the lack of well established function point counting methodologies at the time that the counts were made. The International Function Point Counting Practices Manual is recommended as an current, definitized standard for making function point counts.

The concept of function point to SLOC conversion tables is justified. However, the conversion tables to be used should be based on similar programs developed in similar environments. Universally applicable function point to SLOC conversion tables were not supported by this research.

Finally, there is a need to perform statistical modeling techniques for model function point equations rather than use the standard function point equation. This research definitely supports the concept that transformations of and interactions between the standard function point variables can lead to better models than the standard function point model.

Recommendations for Future Study

There are several areas related to this research which would benefit from additional study. For example, the effects of different SLOC counting methods have on function points ability to model SLOC should be researched. If all the programs under consideration could have the SLOC counted under the various SLOC counting methodologies, it would be possible to perform a similar analysis as in this paper to assess which SLOC counting method provides the best results.

A study of the repeatability of function point counts using the IFPUG User's Counting Practices Manual with different personnel at differing levels

of training would be justified. There may be some subjectivity as to the interpretation of the IFPUG standards leading to variability in the function point counts as counted by different personnel.

Further study into the validity of the use of function points, unadjusted function points, and external function points would be justified. They are all based on functionality, but, may differ in validity and predictability as the type of application differs outside the military environment.

Appendix A: Definition of Terms

Function Point Analysis (FPA): FPA is dependent on the end-user defined functionality of the system. "A function point is defined as one end-user business function" (15:5). More specifically, "initial application requirements statements are examined to determine the number and complexity of various inputs, outputs, calculations, and databases required" which are weighted and then summed to derive a function point count, which is then used to provide an estimate of the software project (31:91).

Software Sizing: "predicting the quantities of source code, specifications, test cases, user documentation, and other tangible deliverables that are the outputs of software projects" (35:2).

International Function Point Users Group (IFPUG): The IFPUG is a group of function point users, mostly from industry, who are providing and maintaining function point counting standards and procedures in an effort to promote consistency in the area of function points (27:v,1).

IFPUG Function Point Counting Practices Manual: "a collection of many interpretations of the rules to a truly coherent document which represents a consensus view of the rules of function point counting" (27:iii).

Software Process Database System (SPDS): The database repository of function point data collected on all Air Force automated data processing projects at the Standard Systems Center (SSC), Gunter AFB, AL. (41:1).

SLOC: "An instruction written in assembler or higher order language is often referred to as a source line of code (SLOC) to differentiate it from a machine instruction" (21:3).

Management Information System (MIS)/ Automated Data Processing Systems (ADP): "System providing uniform organizational information to management in the areas of control, operations, and planning. MIS usually relies on a well-developed data management system, including a data base for helping management reach accurate and rapid organizational decisions" (22:342). Data processing is defined as "sorting, recording, and classifying data for making calculations or decisions" (22:143). For the purposes of this research, MIS and ADP will be used interchangeably since they are used that way in the literature. The idea is to differentiate business oriented systems from highly complex, algorithmic scientific oriented systems as is done in the literature. One author states that non-business applications are "applications that have a higher proportion of logic to functions" (29:26).

Scientific, Embedded (as in embedded algorithms), and Real-time Systems: A system "high in algorithmic complexity but sparse in inputs and outputs... An algorithm is defined as the set of rules which must be completely expressed in order to solve a significant computational problem" (34:82-83). Being more mathematically intense than MIS systems, these systems typically involve parallelism, synchronization, and concurrency processing problems not associated with MIS systems (61:161). Parallelism and concurrent processing mean that computer processing will perform tasks

simultaneously rather than one task at a time. Synchronization carries this concept one step further, meaning that the parallel tasks are completed in a precise timely manner in order to effect the time critical processing required. Examples of this type of software would be observed in the following type systems: missile defense systems, radar navigation packages, telephone switching systems, computer aided design systems, and simulation software (34:81-82). For the purposes of this research, real-time, embedded, and scientific systems will be used interchangeably since they are used that way in the literature.

Validity: "The ability of an instrument (e.g., a test, a questionnaire, an interview, etc.) to actually measure the quality or characteristic it was originally intended to measure" (4:278).

Reliability: "The reliability of a measure refers to its trustworthiness. In other words, it expresses the repeatability, stability, or consistency of the measure. The reliability coefficient, which is typically obtained through use of the simple correlation coefficient (although other methods of computing reliability are possible), indicates how consistent the scores obtained on a measure are" (4:282-283).

Accuracy: According to the 1991 on-line American Heritage Dictionary, accuracy is "having no errors; correct."

Table 10: Appendix Variable Explanation

KSLOC: Kilo-SLOC

FP: adjusted function points

UFP: unadjusted function points

EFP: external function points

CMPLX: a subjective obsolescence complexity factor of 1, 2, or 3

LANGUAGE: an indicator variable denoting that the program is COBOL-only, other single language, or a mixed language program

VAF: the value adjustment factor

OBSOL: the obsolescence complexity factor

LANG: the language indicator; 0 if COBOL-only, 1 if other

VAFLANG: LANG*VAF

OBSLANG: LANG*OBSOL

FPLANG: FP*LANG

UFPOBS: UFP*OBSOL

FPOBS: FP*OBSOL

UV: UFP*VAF

FV: FP*VAF

UL: UFP*LANG

ULV: UFP*LANG*VAF

FPSQRT: $FP^{0.5}$

FPSQOVR: $FP^{(-0.5)}$

FPOVR: $FP^{(-1)}$

UFPSQRT: $UFP^{0.5}$

UFPSQOVR: $UFP^{(-0.5)}$

UFPOVR: $UFP^{(-1)}$

EFPSQRT: $EFP^{0.5}$

EFPSQOVR: $EFP^{(-0.5)}$

EFPOVR: $EFP^{(-1)}$

VAFSQD: VAF^2

LNVAF: natural logarithm of VAF

LNKSLOC: natural logarithm of KSLOC

UVSQD: UFP*VAFSQD

FPSLANG: FPSQRT*LANG

ULVSQD: UFP*LANG*VAFSQD

SLOC: KSLOC*1000

Table 11
SPDS Database

OBS	PRGM	KSLOC	FP	UFP	EFP	CMPLX	LANGUAGE	VAF	OBSOL	LANG
1	SPDS	30.00	2859.04	2672	2106.83	2	1	1.07	16	1
2	SPAS	302.01	16378.20	15165	14965.56	2	1	1.08	16	1
3	CALM	61.00	1095.48	1074	1023.06	1	1	1.02	.	1
4	ATRAS	52.47	385.44	438	247.28	2	0	0.88	16	0
5	AIRMOD	32.70	487.32	524	402.69	1	0	0.93	.	0
6	AFSMWRA	18.52	52.56	73	47.52	2	0	0.72	18	0
7	B-TWRAPS	6.42	549.78	561	516.46	2	0	0.98	17	0
8	CEERS	9.06	105.82	143	[illegible]	1	0	0.7[illegible]	.	0
9	CEMO	30.15	149.10	210	114.31	1	0	0.71	.	0
10	COARS	124.32	2291.10	2182	1937.25	2	0	1.05	18	0
11	CMDS	144.66	2974.14	2542	2817.36	1	0	1.17	.	0
12	CMD-RP	20.17	931.84	896	794.56	1	0	1.04	.	0
13	C-WIMS	596.64	10552.41	8721	8421.60	1	0	1.21	.	0
14	CAMS	4028.06	297312.75	230475	241596.36	3	0	1.29	28	0
15	LOGFOR	38.86	577.68	696	535.35	1	0	0.83	.	0
16	LOGPLAN	32.88	697.48	742	660.82	1	0	0.94	.	0
17	M-TWRAPS	6.39	614.46	627	585.06	2	0	0.98	17	0
18	MMAS	76.40	769.46	974	669.92	2	0	0.79	15	0
19	MDR	9.98	304.95	321	228.80	2	0	0.95	15	0
20	NAFMIS	26.56	352.00	440	312.80	2	0	0.80	22	0
21	NAFMIS-C	5.95	425.60	608	399.70	2	0	0.70	17	0

Table 11 Continued
SPDS Database

OBS	PRGM	KSLOC	FP	UFP	EFP	CMPLX	LANGUAGE	VAF	OBSOL	LANG
22	OLVIMS	771.01	6770.50	6396	5865.20	3	0	1.10	24	0
23	OPSMOD	41.28	881.10	979	774.00	1	0	0.90	.	0
24	PPMS	40.06	1709.68	1988	1619.38	1	0	0.86	.	0
25	RAFAS-A	35.74	100.80	140	95.76	2	0	0.72	18	0
26	RAFAS-B	20.35	107.28	149	102.24	2	0	0.72	18	0
27	T-MIL	11.68	827.52	862	801.60	2	0	0.96	15	0
28	TRAFDIST	73.98	2500.69	2213	2304.07	1	0	1.13	.	0
29	UMERS	8.28	14.28	21	9.52	2	0	0.68	16	0
30	AFSCAPS	157.19	3296.88	2892	2823.78	2	2	1.14	19	1
31	AFORMS	265.60	3171.37	3079	2811.90	3	2	1.03	24	1
32	ADRSS	22.20	199.95	215	153.45	[illegible]	2	0.93	23	1
33	BMDS-M	26.35	258.96	249	227.76	2	2	1.04	19	1
34	BMDS	31.63	390.10	415	346.86	2	2	0.94	14	1
35	BLISS	91.89	1595.16	1477	1434.24	2	2	1.08	16	1
36	BLAMES	23.51	89.27	113	61.62	2	2	0.79	14	1
37	BASE-WIM	655.58	9506.70	7545	8399.16	1	2	1.26	.	1
38	BBAS	18.86	1825.95	1739	1599.15	2	2	1.05	18	1
39	BCAS	277.43	4958.40	4132	4314.00	3	2	1.20	23	1
40	CBAS-I	169.67	4613.44	4436	4304.56	2	2	1.04	17	1
41	CBAS-II	375.50	16627.82	13742	13510.86	2	2	1.21	22	1
42	CSS	100.16	1719.39	1549	1548.45	2	2	1.11	18	1

Table 11 Continued
SPDS Database

OBS	PRGM	KSLOC	FP	UFP	EFP	CMPLX	LANGUAGE	VAF	OBSOL	LANG
43	DDS	83.00	1028.61	1039	952.38	2	2	0.99	22	1
44	DMARS	71.29	1814.58	1779	1743.18	2	2	1.02	21	1
45	DMS1100-	361.85	556.25	625	500.18	3	2	0.89	26	1
46	GAFS	774.63	9184.00	8896	9117.92	3	2	1.12	28	1
47	LOGMOD-B	240.98	1885.95	1905	1810.71	1	2	0.99	.	1
48	MAMS	38.02	247.64	302	151.70	2	2	0.82	18	1
49	MEDLOG	514.67	5554.26	4707	5015.00	2	2	1.18	22	1
50	SMAS	480.21	3233.44	2887	2653.28	2	1	1.12	21	1
51	S1100-UT	21.59	249.30	277	212.40	2	2	0.90	21	1
52	SBSS	1501.61	40371.92	32558	38232.92	3	2	1.24	25	1
53	SIMS	608.98	6201.09	5211	5814.34	3	2	1.19	23	1
54	UTILS	10.57	.	423	.	2	2	0.65	14	1
55	IO-AUTOD	36.06	.	1096	.	2	1	0.65	14	1
56	HAMPS	76.85	660.38	623	588.30	3	1	1.06	24	1
55	IO-AUTOD	36.06	.	1096	.	2	1	0.65	14	1
56	HAMPS	76.85	660.38	623	588.30	3	1	1.06	24	1
57	PDS	26.64	.	1111	.	2	1	0.65	20	1
58	SIS	756.00	430.55	545	273.34	2	1	0.79	19	1
59	RIMS	19.79	.	727	.	2	2	.	17	1
60	PDOS	78.88	.	6887	.	2	0	.	15	0
61	IPMS	122.35	.	9304	.	1	2	1.11	.	1

TABLE 12
Commercial Database

OBS	PROJECT	LANGUAGE	KSLOC	UFP	FP	VAF
1	1	COBOL	130	1750	1750	1.00
2	2	COBOL	318	1902	1902	1.00
3	3	COBOL	20	522	428	0.82
4	4	PL/1	54	660	759	1.15
5	5	COBOL	62	479	431	0.90
6	6	COBOL	28	377	283	0.75
7	7	COBOL	35	256	205	0.80
8	8	COBOL	30	263	289	1.10
9	9	COBOL	48	716	680	0.95
10	10	COBOL	93	690	794	1.15
11	11	COBOL	57	465	512	1.10
12	12	COBOL	22	299	224	0.75
13	13	COBOL	24	491	417	0.85
14	14	PL/1	42	802	682	0.85
15	15	COBOL	40	220	209	0.95
16	16	COBOL	96	488	512	1.05
17	17	PL/1	40	551	606	1.10
18	18	COBOL	52	364	400	1.10
19	19	COBOL	94	1074	1235	1.15
20	20	PL/1	110	1310	1572	1.20
21	21	COBOL	15	476	500	1.05
22	22	DMS	24	694	694	1.00
23	23	DMS	3	166	199	1.20

TABLE 12 Continued
Commercial Database

OBS	PROJECT	LANGUAGE	KSLOC	UFP	FP	VAF
24	24	COBOL	29	263	260	0.99
25	25	COBOL	254	1010	1217	1.20
26	26	COBOL	214	881	788	0.89
27	27	COBOL	254	1603	1611	1.00
28	28	COBOL	41	457	507	1.11
29	29	COBOL	450	2284	2307	1.01
30	30	COBOL	450	1583	1338	0.85
31	31	BLISS	50	411	421	1.02
32	32	COBOL	43	97	100	1.03
33	33	COBOL	200	998	993	0.99
34	34	COBOL	39	250	240	0.96
35	35	COBOL	129	724	789	1.00
36	36	COBOL	289	1554	1593	1.09
37	37	COBOL	161	705	691	0.98
38	38	COBOL	165	1375	1348	0.98
39	39	NATURAL	60	976	1044	1.07

Table 13
Outlier Data Analysis for the Military Database

Obs	Dep Var KSLOC	Predict Value	Std Err Predict	Lower95% Predict	Upper95% Predict	Residual
1	30.0000	212.4	35.472	-167.7	592.5	-182.4
2	302.0	677.0	67.430	279.9	1074.2	-375.0
3	61.0000	162.2	38.284	-219.0	543.4	-101.2
4	52.4700	72.1772	37.354	-308.7	453.0	-19.7072
5	32.7000	74.7445	37.328	-306.1	455.6	-42.0445
6	18.5200	68.8771	37.388	-312.0	449.7	-50.3571
7	6.4200	76.6240	37.309	-304.2	457.5	-70.2040
8	9.0600	69.1679	37.385	-311.7	450.0	-60.1079
9	30.1500	69.9805	37.377	-310.9	450.8	-39.8305
10	124.3	100.1	37.090	-280.7	480.8	24.2247
11	144.7	114.6	36.970	-266.1	495.3	30.0253
12	20.1700	81.2182	37.263	-299.6	462.0	-61.0482
13	596.6	207.2	36.511	-173.3	587.7	389.4
14	4028.1	4059.2	185.827	3531.4	4587.1	-31.1848
15	38.8600	76.9361	37.306	-303.9	457.8	-38.0761
16	32.8800	79.0088	37.285	-301.8	459.8	-46.1288
17	6.3900	77.7573	37.297	-303.1	458.6	-71.3673
18	76.4000	79.1591	37.283	-301.7	460.0	-2.7591
19	9.9800	71.8719	37.357	-309.0	452.7	-61.8919
20	26.5600	73.2595	37.343	-307.6	454.1	-46.6995
21	5.9500	74.6951	37.328	-306.1	455.5	-68.7451
22	771.0	165.0	36.655	-215.6	545.6	606.0
23	41.2800	80.8785	37.267	-299.9	461.7	-39.5985
24	40.0600	94.8441	37.136	-285.9	475.6	-54.7841
25	35.7400	69.6741	37.380	-311.2	450.5	-33.9341
26	20.3500	69.7811	37.379	-311.1	450.6	-49.4311
27	11.6800	81.3345	37.262	-299.5	462.1	-69.6545
28	73.9800	106.2	37.038	-274.6	486.9	-32.1752
29	8.2800	68.2494	37.395	-312.6	449.1	-59.9694
30	157.2	228.7	35.224	-151.4	608.7	-71.4736
31	265.6	232.2	35.044	-147.7	612.2	33.3572
32	22.2000	130.5	40.449	-251.6	512.6	-108.3
33	26.3500	132.4	40.356	-249.7	514.5	-106.1
34	31.6300	137.7	39.910	-244.2	519.6	-106.1
35	91.8900	177.1	37.415	-203.7	558.0	-85.2502
36	23.5100	126.9	40.732	-255.3	509.2	-103.4
37	655.6	414.7	38.789	33.2819	796.1	240.9
38	18.8600	185.2	36.905	-195.5	565.8	-166.3
39	277.4	278.3	34.540	-101.5	658.1	-0.8871
40	169.7	284.3	34.561	-95.4880	664.1	-114.6
41	375.5	624.3	61.097	231.2	1017.3	-248.8
42	100.2	180.5	37.271	-200.3	561.3	-80.3206
43	83.0000	160.3	38.364	-220.9	541.6	-77.3369
44	71.2900	188.3	36.831	-192.3	569.0	-117.1
45	361.9	144.5	39.365	-237.2	526.2	217.3
46	774.6	453.9	42.516	70.8345	836.9	320.8
47	241.0	192.0	36.606	-188.6	572.6	48.9794
48	38.0200	132.2	40.212	-249.8	514.3	-94.2100
49	514.7	301.5	34.641	-78.3095	681.3	213.2
50	480.2	225.7	35.229	-154.3	605.8	254.5
51	21.5900	132.7	40.280	-249.3	514.8	-111.1
52	1501.6	1412.6	153.681	928.2	1896.9	89.0448

Obs	Dep Var KSLOC	Predict Value	Std Err Predict	Lower95% Predict	Upper95% Predict	Residual
53	609.0	324.9	34.948	-55.0421	704.8	284.1
54	10.5700	.	.	.	.	.
55	36.0600	.	.	.	.	.
56	76.8500	145.9	39.371	-235.7	527.6	-69.0734
57	26.6400	.	.	.	.	.
58	756.0	139.1	39.570	-242.6	520.9	616.9
59	19.7900	.	.	.	.	.
60	78.8800	.	.	.	.	.
61	122.4	.	.	.	.	.

Obs	Std Err Residual	Student Residual	-2-1-0 1 2	Cook's D	Rstudent	Hat Diag H
1	182.579	-0.999	*	0.009	-0.9989	0.0364
2	173.339	-2.164	****	0.177	-2.2478	0.1314
3	182.010	-0.556	*	0.003	-0.5523	0.0424
4	182.203	-0.108		0.000	-0.1071	0.0403
5	182.208	-0.231		0.001	-0.2286	0.0403
6	182.196	-0.276		0.001	-0.2739	0.0404
7	182.212	-0.385		0.002	-0.3820	0.0402
8	182.197	-0.330		0.001	-0.3270	0.0404
9	182.198	-0.219		0.001	-0.2166	0.0404
10	182.257	0.133		0.000	0.1316	0.0398
11	182.281	0.165		0.000	0.1631	0.0395
12	182.222	-0.335		0.001	-0.3321	0.0401
13	182.374	2.135	****	0.046	2.2156	0.0385
14	7.855	-3.970	******	2204.903	-4.7288	0.9982
15	182.213	-0.209		0.000	-0.2070	0.0402
16	182.217	-0.253		0.001	-0.2508	0.0402
17	182.215	-0.392		0.002	-0.3884	0.0402
18	182.217	-0.015		0.000	-0.0150	0.0402
19	182.202	-0.340		0.001	-0.3367	0.0403
20	182.205	-0.256		0.001	-0.2539	0.0403
21	182.208	-0.377		0.001	-0.3741	0.0403
22	182.345	3.324	******	0.112	3.7179	0.0388
23	182.221	-0.217		0.000	-0.2153	0.0401
24	182.248	-0.301		0.001	-0.2979	0.0399
25	182.198	-0.186		0.000	-0.1845	0.0404
26	182.198	-0.271		0.001	-0.2688	0.0404
27	182.222	-0.382		0.002	-0.3790	0.0401
28	182.267	-0.177		0.000	-0.1748	0.0397
29	182.195	-0.329		0.001	-0.3263	0.0404
30	182.627	-0.391		0.001	-0.3881	0.0359
31	182.661	0.183		0.000	0.1809	0.0355
32	181.541	-0.597	*	0.004	-0.5928	0.0473
33	181.562	-0.584	*	0.004	-0.5804	0.0471
34	181.660	-0.584	*	0.004	-0.5803	0.0460
35	182.190	-0.468		0.002	-0.4643	0.0405
36	181.478	-0.570	*	0.004	-0.5660	0.0480
37	181.903	1.324	**	0.020	1.3343	0.0435
38	182.294	-0.912	*	0.009	-0.9107	0.0394
39	182.757	-0.005		0.000	-0.0048	0.0345
40	182.753	-0.627	*	0.004	-0.6235	0.0345
41	175.671	-1.416	**	0.061	-1.4306	0.1079
42	182.220	-0.441		0.002	-0.4373	0.0402
43	181.993	-0.425		0.002	-0.4215	0.0425

<table>
<tr><th>Obs</th><th>Std Err Residual</th><th>Student Residual</th><th>-2-1-0 1 2</th><th>Cook's D</th><th>Rstudent</th><th>Hat Diag H</th></tr>
<tr><td>44</td><td>182.309</td><td>-0.642</td><td>| *| |</td><td>0.004</td><td>-0.6383</td><td>0.0392</td></tr>
<tr><td>45</td><td>181.779</td><td>1.196</td><td>| |** |</td><td>0.017</td><td>1.2008</td><td>0.0448</td></tr>
<tr><td>46</td><td>181.068</td><td>1.772</td><td>| |*** |</td><td>0.043</td><td>1.8107</td><td>0.0523</td></tr>
<tr><td>47</td><td>182.355</td><td>0.269</td><td>| | |</td><td>0.001</td><td>0.2661</td><td>0.0387</td></tr>
<tr><td>48</td><td>181.594</td><td>-0.519</td><td>| *| |</td><td>0.003</td><td>-0.5150</td><td>0.0467</td></tr>
<tr><td>49</td><td>182.738</td><td>1.166</td><td>| |** |</td><td>0.012</td><td>1.1707</td><td>0.0347</td></tr>
<tr><td>50</td><td>182.626</td><td>1.393</td><td>| |** |</td><td>0.018</td><td>1.4067</td><td>0.0359</td></tr>
<tr><td>51</td><td>181.579</td><td>-0.612</td><td>| *| |</td><td>0.005</td><td>-0.6083</td><td>0.0469</td></tr>
<tr><td>52</td><td>104.764</td><td>0.850</td><td>| |* |</td><td>0.389</td><td>0.8476</td><td>0.6827</td></tr>
<tr><td>53</td><td>182.680</td><td>1.555</td><td>| |*** |</td><td>0.022</td><td>1.5777</td><td>0.0353</td></tr>
<tr><td>54</td><td>.</td><td>.</td><td></td><td>.</td><td>.</td><td>.</td></tr>
<tr><td>55</td><td>.</td><td>.</td><td></td><td>.</td><td>.</td><td>.</td></tr>
<tr><td>56</td><td>181.778</td><td>-0.380</td><td>| | |</td><td>0.002</td><td>-0.3768</td><td>0.0448</td></tr>
<tr><td>57</td><td>.</td><td>.</td><td></td><td>.</td><td>.</td><td>.</td></tr>
<tr><td>58</td><td>181.735</td><td>3.394</td><td>| |******|</td><td>0.137</td><td>3.8199</td><td>0.0453</td></tr>
<tr><td>59</td><td>.</td><td>.</td><td></td><td>.</td><td>.</td><td>.</td></tr>
<tr><td>60</td><td>.</td><td>.</td><td></td><td>.</td><td>.</td><td>.</td></tr>
<tr><td>61</td><td>.</td><td>.</td><td></td><td>.</td><td>.</td><td>.</td></tr>
</table>

Obs	Cov Ratio	Dffits	INTERCEP Dfbetas	EFP Dfbetas	LANG Dfbetas	UL Dfbetas
1	1.0379	-0.1941	-0.0005	0.0023	-0.1347	0.0432
2	0.8479	-0.8744	-0.0042	0.0188	0.0243	-0.7434
3	1.1032	-0.1162	0.0001	-0.0005	-0.0852	0.0495
4	1.1269	-0.0220	-0.0220	0.0047	0.0148	-0.0008
5	1.1232	-0.0468	-0.0468	0.0099	0.0316	-0.0017
6	1.1213	-0.0562	-0.0562	0.0123	0.0379	-0.0021
7	1.1147	-0.0782	-0.0782	0.0164	0.0527	-0.0027
8	1.1184	-0.0671	-0.0671	0.0147	0.0452	-0.0025
9	1.1238	-0.0444	-0.0444	0.0097	0.0299	-0.0016
10	1.1257	0.0268	0.0268	-0.0049	-0.0180	0.0008
11	1.1246	0.0331	0.0330	-0.0054	-0.0223	0.0009
12	1.1178	-0.0679	-0.0679	0.0139	0.0458	-0.0023
13	0.7741	0.4436	0.4365	-0.0195	-0.2938	0.0033
14	138.3314	-111.865	2.7653	-109.688	-2.4812	18.3193
15	1.1239	-0.0424	-0.0424	0.0089	0.0286	-0.0015
16	1.1221	-0.0513	-0.0513	0.0106	0.0346	-0.0018
17	1.1143	-0.0795	-0.0795	0.0166	0.0536	-0.0028
18	1.1277	-0.0031	-0.0031	0.0006	0.0021	-0.0001
19	1.1178	-0.0690	-0.0690	0.0149	0.0465	-0.0025
20	1.1221	-0.0520	-0.0520	0.0111	0.0351	-0.0019
21	1.1153	-0.0766	-0.0766	0.0163	0.0517	-0.0027
22	0.4242	0.7474	0.7417	-0.0738	-0.4995	0.0123
23	1.1235	-0.0440	-0.0440	0.0090	0.0297	-0.0015
24	1.1194	-0.0607	-0.0607	0.0114	0.0409	-0.0019
25	1.1249	-0.0378	-0.0378	0.0083	0.0255	-0.0014
26	1.1215	-0.0552	-0.0552	0.0120	0.0372	-0.0020
27	1.1148	-0.0775	-0.0775	0.0158	0.0522	-0.0026
28	1.1244	-0.0355	-0.0355	0.0062	0.0239	-0.0010
29	1.1185	-0.0670	-0.0670	0.0148	0.0451	-0.0025
30	1.1093	-0.0749	-0.0000	0.0001	-0.0515	0.0145
31	1.1193	0.0347	0.0000	-0.0002	0.0236	-0.0058
32	1.1048	-0.1321	0.0002	-0.0008	-0.0976	0.0679

Obs	Cov Ratio	Dffits	INTERCEP Dfbetas	EFP Dfbetas	LANG Dfbetas	UL Dfbetas
33	1.1058	-0.1290	0.0002	-0.0009	-0.0954	0.0659
34	1.1046	-0.1275	0.0002	-0.0007	-0.0942	0.0631
35	1.1088	-0.0954	0.0001	-0.0003	-0.0694	0.0362
36	1.1083	-0.1270	0.0002	-0.0008	-0.0940	0.0665
37	0.9839	0.2845	-0.0003	0.0014	0.1059	0.1275
38	1.0550	-0.1844	0.0000	-0.0001	-0.1332	0.0641
39	1.1211	-0.0009	0.0000	-0.0000	-0.0006	0.0000
40	1.0869	-0.1179	-0.0002	0.0009	-0.0714	-0.0043
41	1.0335	-0.4975	-0.0024	0.0108	-0.0093	-0.4063
42	1.1106	-0.0894	0.0001	-0.0004	-0.0650	0.0332
43	1.1146	-0.0889	0.0001	-0.0003	-0.0652	0.0382
44	1.0906	-0.1290	0.0001	-0.0003	-0.0931	0.0442
45	1.0114	0.2600	-0.0002	0.0010	0.1917	-0.1232
46	0.8859	0.4252	0.0010	-0.0046	0.1150	0.2452
47	1.1197	0.0534	-0.0000	0.0001	0.0384	-0.0175
48	1.1117	-0.1141	0.0001	-0.0005	-0.0843	0.0577
49	1.0064	0.2219	-0.0001	0.0004	0.1307	0.0168
50	0.9613	0.2714	0.0003	-0.0014	0.1865	-0.0525
51	1.1027	-0.1349	0.0002	-0.0008	-0.0997	0.0686
52	3.2225	1.2434	-0.0024	0.0108	-0.3084	1.1927
53	0.9239	0.3018	-0.0005	0.0020	0.1673	0.0450
54	.	.	.	.	.	.
55	.	.	.	.	.	.
56	1.1204	-0.0816	0.0001	-0.0005	-0.0602	0.0387
57	.	.	.	.	.	.
58	0.4071	0.8317	-0.0002	0.0009	0.6133	-0.4003
59	.	.	.	.	.	.
60	.	.	.	.	.	.
61	.	.	.	.	.	.

Sum of Residuals 0
Sum of Squared Residuals 1764255.0796
Predicted Resid SS (Press) 307677609.01

Table 14

Outlier Data Analysis for the Commercial Database

Obs	Dep Var KSLOC	Predict Value	Std Err Predict	Lower95% Predict	Upper95% Predict	Residual
1	130.0	301.8	19.781	179.7	423.9	-171.8
2	318.0	329.7	22.089	206.0	453.5	-11.7475
3	20.0000	75.2668	16.961	-45.0546	195.6	-55.2668
4	54.0000	42.1486	19.297	-79.6149	163.9	11.8514
5	62.0000	67.6411	12.932	-50.5996	185.9	-5.6411
6	28.0000	48.3466	21.965	-75.2655	172.0	-20.3466
7	35.0000	26.2668	19.444	-95.5928	148.1	8.7332
8	30.0000	28.6190	16.233	-91.2880	148.5	1.3810
9	48.0000	111.4	10.461	-5.8160	228.6	-63.4131
10	93.0000	107.3	16.309	-12.6088	227.3	-14.3402
11	57.0000	65.7755	14.500	-53.2126	184.8	-8.7755
12	22.0000	33.9990	22.303	-89.8623	157.9	-11.9990
13	24.0000	69.6710	15.314	-49.7364	189.1	-45.6710
14	42.0000	54.3653	27.159	-73.4301	182.2	-12.3653
15	40.0000	20.1771	13.813	-98.4736	138.8	19.8229
16	96.0000	69.8288	12.184	-48.0843	187.7	26.1712
17	40.0000	31.7765	16.258	-88.1445	151.7	8.2235
18	52.0000	47.1972	15.292	-72.1985	166.6	4.8028
19	94.0000	178.0	16.700	57.8038	298.1	-83.9745
20	110.0	103.1	35.838	-33.2065	239.4	6.8799
21	15.0000	67.6215	12.273	-50.3295	185.6	-52.6215
22	24.0000	44.7964	18.880	-76.6975	166.3	-20.7964
23	3.0000	-3.8775	21.494	-127.1	119.4	6.8775
24	29.0000	28.2286	13.152	-90.1122	146.6	0.7714
25	254.0	166.4	19.608	44.4115	288.3	87.6204
26	214.0	141.6	13.020	23.2705	259.8	72.4491
27	254.0	274.7	17.635	154.0	395.5	-20.7484
28	41.0000	64.3395	15.074	-54.9421	183.6	-23.3395
29	450.0	400.0	28.104	271.4	528.7	49.9507
30	450.0	270.5	21.312	147.4	393.7	179.5
31	50.0000	18.3985	13.680	-100.2	137.0	31.6015
32	43.0000	-2.1640	15.728	-121.8	117.5	45.1640
33	200.0	163.4	10.794	46.0738	280.8	36.5729
34	39.0000	25.7309	13.364	-92.7078	144.2	13.2691
35	129.0	113.1	10.028	-4.0108	230.1	15.9379
36	289.0	266.1	18.226	145.0	387.1	22.9455
37	161.0	109.5	10.037	-7.5799	226.6	51.5038
38	165.0	232.7	14.663	113.7	351.8	-67.7383
39	60.0000	71.4200	25.644	-55.0781	197.9	-11.4200

Obs	Std Err Residual	Student Residual	-2-1-0 1 2	Cook's D	Rstudent	Hat Diag H
1	53.234	-3.227	******	0.359	-3.7949	0.1213
2	52.318	-0.225		0.002	-0.2215	0.1513
3	54.198	-1.020	**	0.025	-1.0203	0.0892
4	53.411	0.222		0.002	0.2189	0.1155
5	55.298	-0.102		0.000	-0.1006	0.0519
6	52.371	-0.389		0.007	-0.3837	0.1496
7	53.358	0.164		0.001	0.1614	0.1172
8	54.421	0.025		0.000	0.0250	0.0817
9	55.818	-1.136	**	0.011	-1.1409	0.0339
10	54.398	-0.264		0.002	-0.2601	0.0825
11	54.908	-0.160		0.000	-0.1576	0.0652

Obs	Std Err Residual	Student Residual	-2-1-0 1 2	Cook's D	Rstudent	Hat Diag H
12	52.227	-0.230	| | |	0.002	-0.2266	0.1542
13	54.686	-0.835	| *| |	0.014	-0.8315	0.0727
14	49.875	-0.248	| | |	0.005	-0.2446	0.2287
15	55.085	0.360	| | |	0.002	0.3553	0.0592
16	55.468	0.472	| | |	0.003	0.4665	0.0460
17	54.413	0.151	| | |	0.001	0.1490	0.0820
18	54.693	0.088	| | |	0.000	0.0866	0.0725
19	54.279	-1.547	| ***| |	0.057	-1.5798	0.0865
20	44.054	0.156	| | |	0.004	0.1540	0.3982
21	55.448	-0.949	| *| |	0.011	-0.9476	0.0467
22	53.560	-0.388	| | |	0.005	-0.3835	0.1105
23	52.565	0.131	| | |	0.001	0.1290	0.1432
24	55.246	0.014	| | |	0.000	0.0138	0.0536
25	53.298	1.644	| |*** |	0.091	1.6868	0.1192
26	55.278	1.311	| |** |	0.024	1.3247	0.0526
27	53.983	-0.384	| | |	0.004	-0.3796	0.0964
28	54.753	-0.426	| | |	0.003	-0.4212	0.0705
29	49.348	1.012	| |** |	0.083	1.0126	0.2449
30	52.639	3.409	| |******|	0.476	4.1116	0.1408
31	55.118	0.573	| |* |	0.005	0.5678	0.0580
32	54.569	0.828	| |* |	0.014	0.8238	0.0767
33	[illegible]	0.656	| |* |	0.004	0.6505	0.0361
34	[illegible]	0.240	| | |	0.001	0.2371	0.0554
35	[illegible]	0.285	| | |	0.001	0.2814	0.0312
36	53.786	0.427	| | |	0.005	0.4216	0.1030
37	55.896	0.921	| |* |	0.007	0.9194	0.0312
38	54.865	-1.235	| **| |	0.027	-1.2443	0.0667
39	50.671	-0.225	| | |	0.003	-0.2223	0.2039

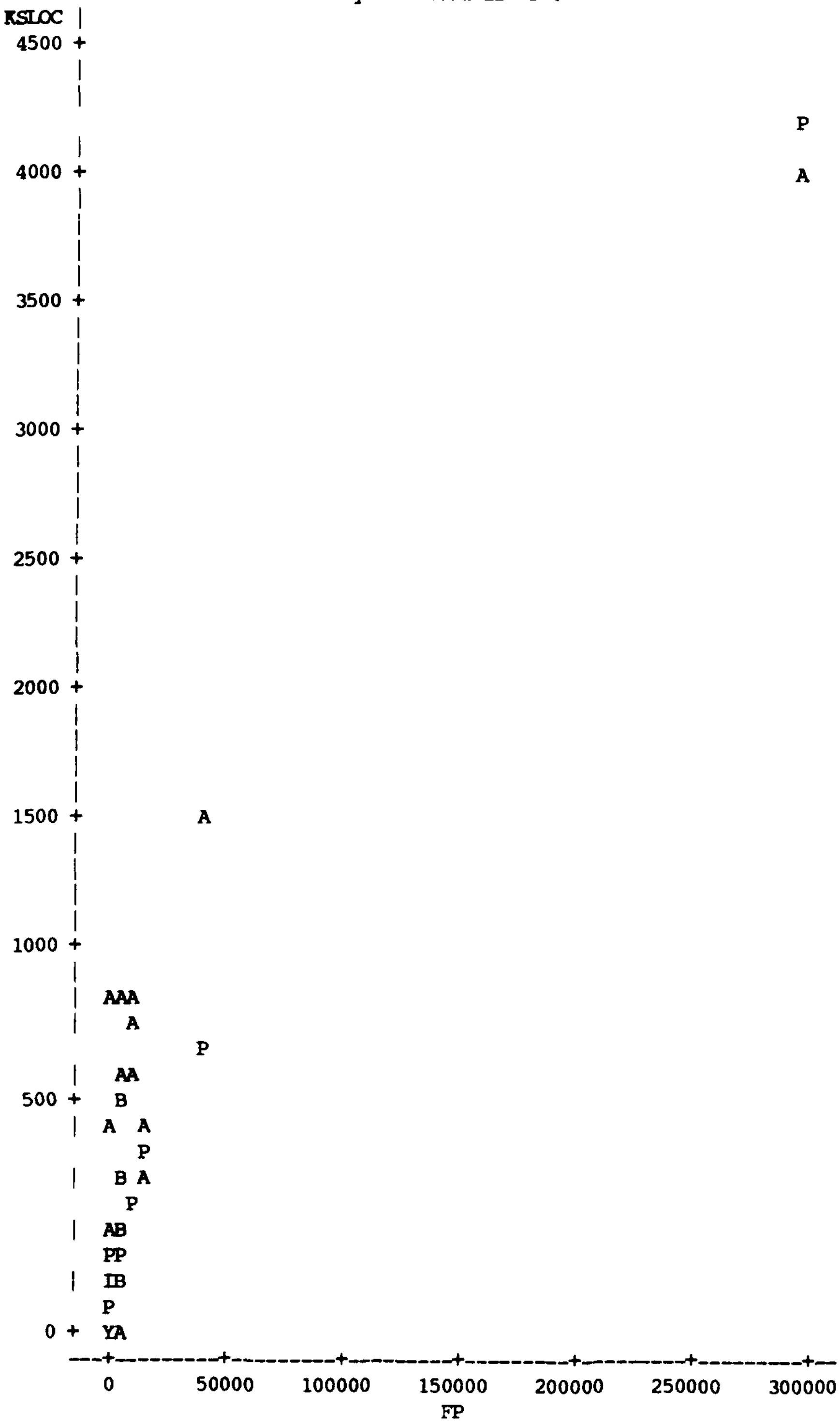
Obs	Cov Ratio	Dffits	INTERCEP Dfbetas	UFP Dfbetas	VAF Dfbetas	UL Dfbetas
1	0.3112	-1.4102	0.0605	-1.2165	0.0520	0.3428
2	1.3155	-0.0935	0.0044	-0.0834	0.0041	0.0208
3	1.0928	-0.3193	-0.2776	0.0541	0.2466	0.0062
4	1.2624	0.0791	-0.0284	-0.0148	0.0322	0.0510
5	1.1829	-0.0235	-0.0156	0.0076	0.0121	0.0035
6	1.2978	-0.1609	-0.1493	0.0357	0.1351	-0.0087
7	1.2682	0.0588	0.0503	-0.0222	-0.0432	0.0008
8	1.2228	0.0075	-0.0031	-0.0043	0.0044	-0.0027
9	1.0002	-0.2138	-0.0897	0.0093	0.0629	0.0635
10	1.2142	-0.0780	0.0532	0.0112	-0.0614	0.0343
11	1.1978	-0.0416	[illegible]	0.0169	-0.0265	0.0172
12	1.3197	-0.0968	-0.0888	0.0270	0.0794	-0.0054
13	1.1173	-0.2328	-0.1893	0.0551	0.1622	0.0140
14	1.4457	-0.1332	-0.0838	-0.0042	0.0847	-0.1112
15	1.1760	0.0891	0.0325	-0.0583	-0.0148	-0.0179
16	1.1475	0.1025	-0.0259	-0.0431	0.0439	-0.0420
17	1.2200	0.0445	-0.0098	-0.0137	0.0134	0.0282
18	1.2097	0.0242	-0.0108	-0.0121	0.0149	-0.0094
19	0.9259	-0.4860	0.3382	-0.1249	-0.3565	0.2160
20	1.8609	0.1253	-0.0265	0.0228	0.0205	0.1059
21	1.0613	-0.2098	0.0524	0.0910	-0.0896	0.0853
22	1.2409	-0.1352	-0.0350	0.0142	0.0312	-0.1181

Obs	Cov Ratio	Dffits	INTERCEP Dfbetas	UFP Dfbetas	VAF Dfbetas	UL Dfbetas
23	1.3081	0.0527	-0.0326	-0.0293	0.0402	-0.0072
24	1.1866	0.0033	0.0005	-0.0021	0.0002	-0.0009
25	0.9244	0.6206	-0.4881	0.0894	0.5165	-0.2658
26	0.9691	0.3120	0.2117	0.0679	-0.1942	-0.0478
27	1.2219	-0.1240	0.0046	-0.1021	0.0035	0.0331
28	1.1832	-0.1160	0.0593	0.0468	-0.0772	0.0477
29	1.3205	0.5767	-0.0477	0.5381	-0.0159	-0.1101
30	0.2601	1.6647	0.8613	1.1919	-0.9673	-0.1282
31	1.1480	0.1409	0.0199	-0.0690	-0.0017	0.0810
32	1.1238	0.2375	-0.0154	-0.1772	0.0642	-0.0654
33	1.1088	0.1259	0.0106	0.0482	-0.0040	-0.0480
34	1.1809	0.0574	0.0181	-0.0369	-0.0067	-0.0129
35	1.1483	0.0505	0.0025	-0.0034	0.0044	-0.0208
36	1.2260	0.1429	-0.0595	0.1021	0.0527	-0.0511
37	1.0507	0.1651	0.0341	-0.0142	-0.0111	-0.0611
38	1.0068	-0.3325	-0.0271	-0.2432	0.0392	0.0942
39	1.4024	-0.1125	-0.0037	-0.0091	0.0061	-0.1020

Sum of Residuals	0
Sum of Squared Residuals	112879.1419
Predicted Resid SS (Press)	143341.0896

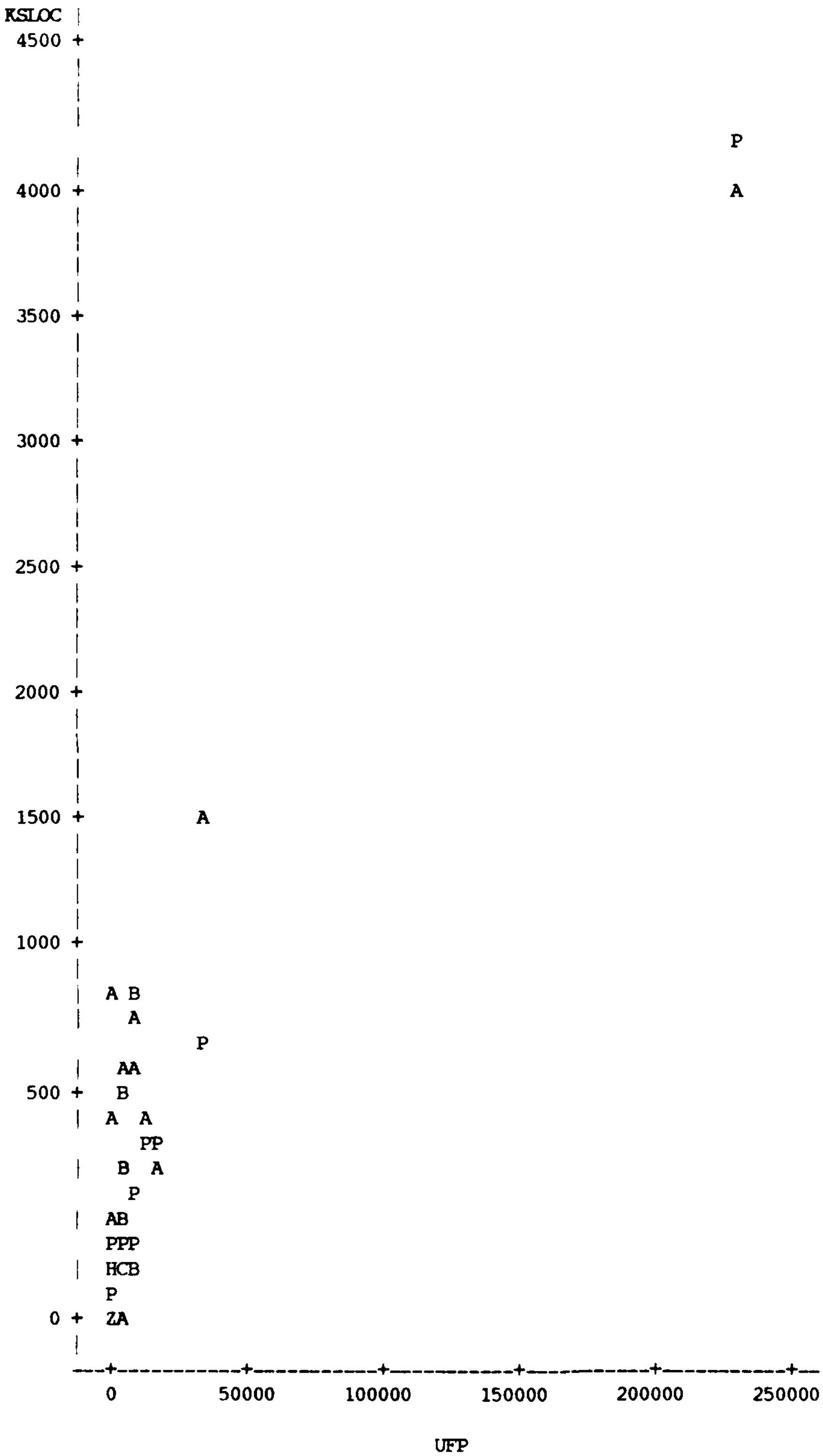
Table 15
Transformation Analysis of SPDS Data

Plot of KSLOC*FP. Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT1*FP. Symbol used is 'P'.

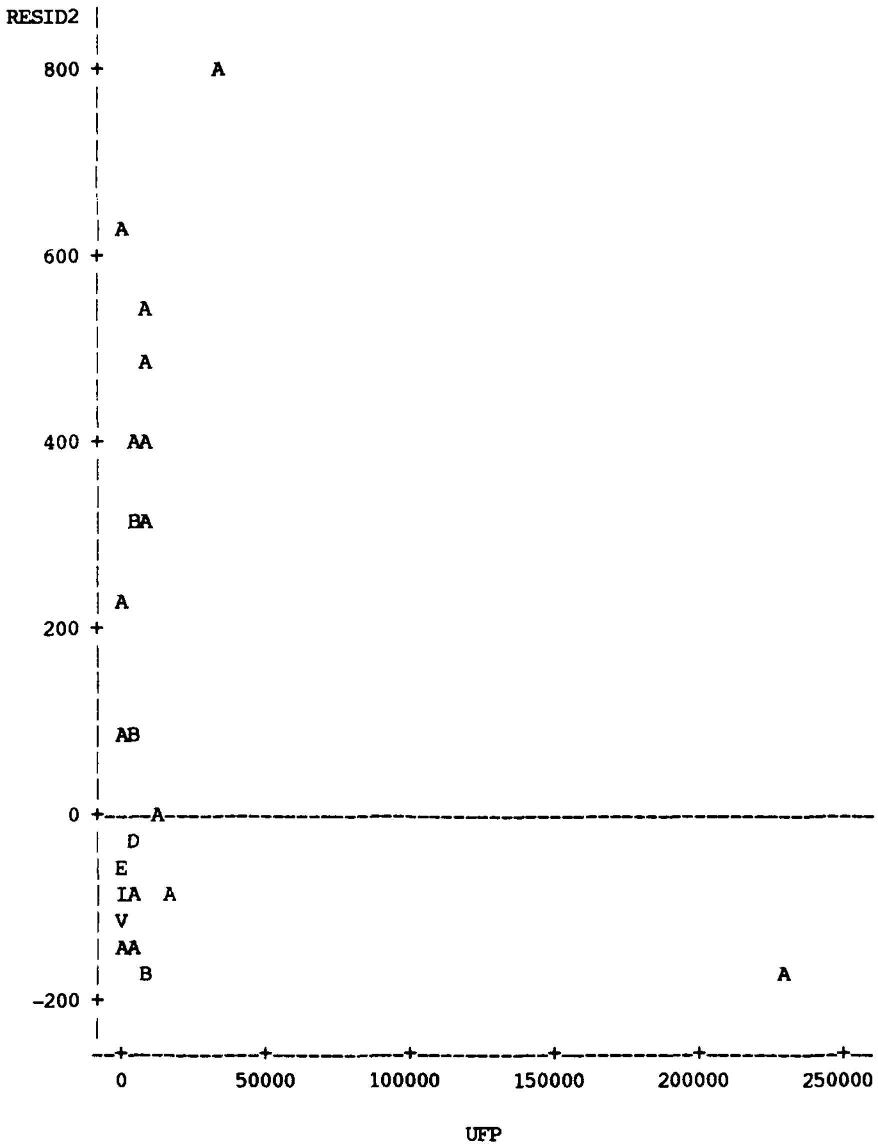


```
          Plot of RESID1*FP.  Legend: A = 1 obs, B = 2 obs, etc.

RESID1 |
       |
   800 +        A
       |
       |
       |
       |
       |
       |
   600 + A
       |
       |  A
       |   A
       |
       |
       |
   400 +
       |  AA
       |
       |   A
       |  B
       |
       |
   200 + A
       |
       |
       |
       |  A
       | AA
       |
     0 +----A------------------------------------------------------
       |  C
       | B  A
       | G
       | PA
       | IA
       |                                                        A
  -200 +
       |
       --+---------+---------+---------+---------+---------+---------+--
         0       50000    100000    150000    200000    250000    300000

                                  FP
```

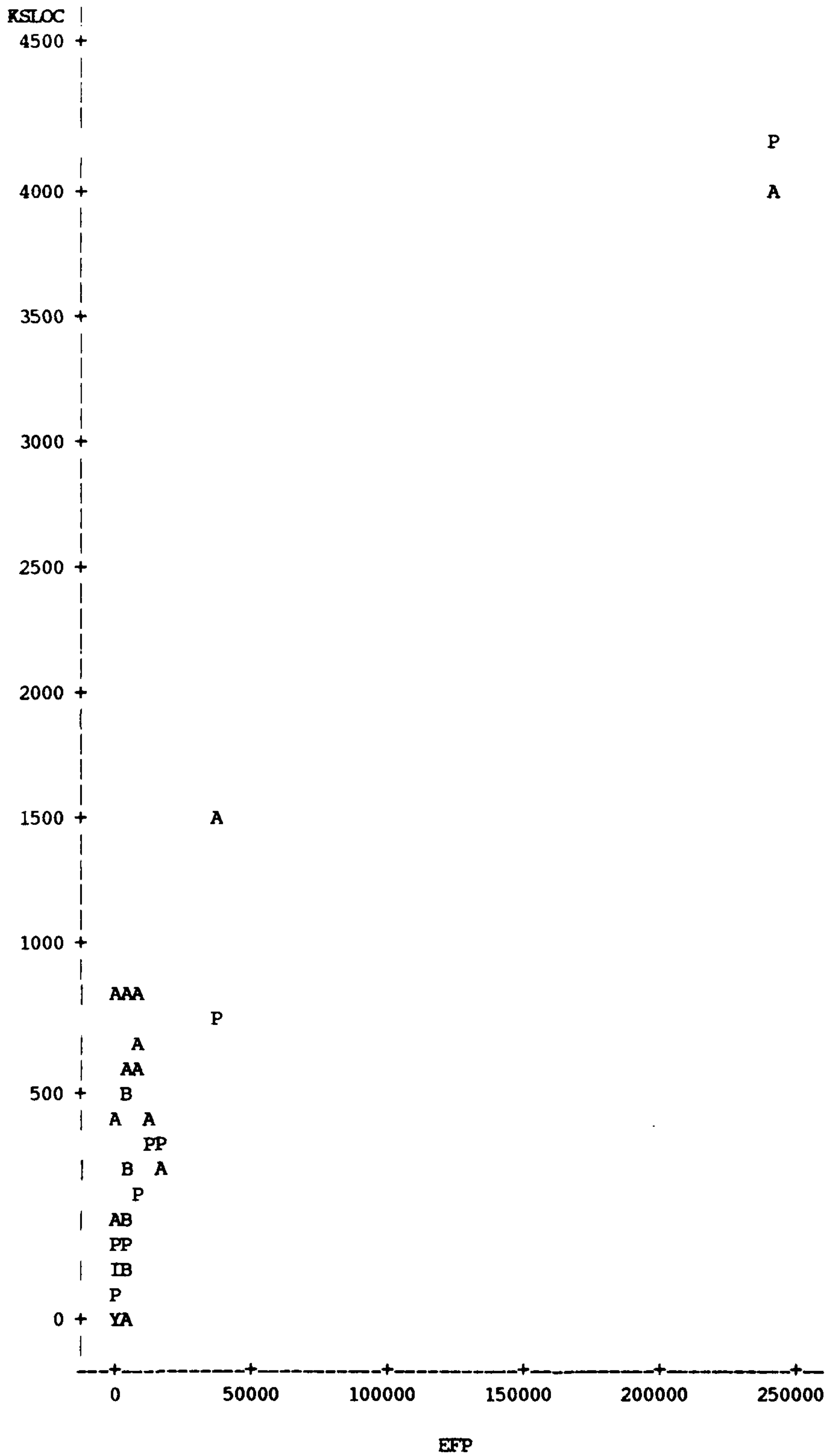
Plot of KSLOC*UFP.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT2*UFP. Symbol used is 'P'.



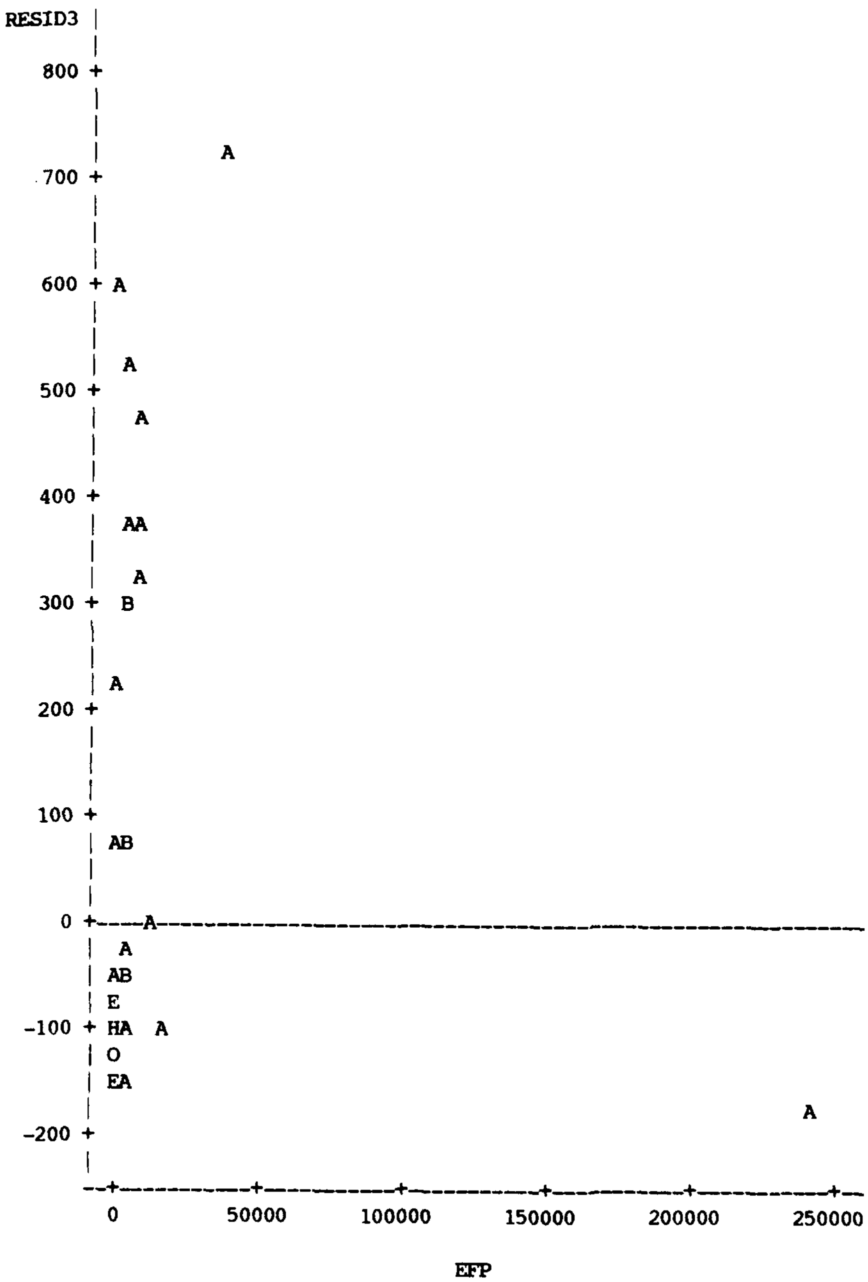
Plot of RESID2*UFP. Legend: A = 1 obs, B = 2 obs, etc.



Plot of KSLOC*EFP.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT3*EFP. Symbol used is 'P'.

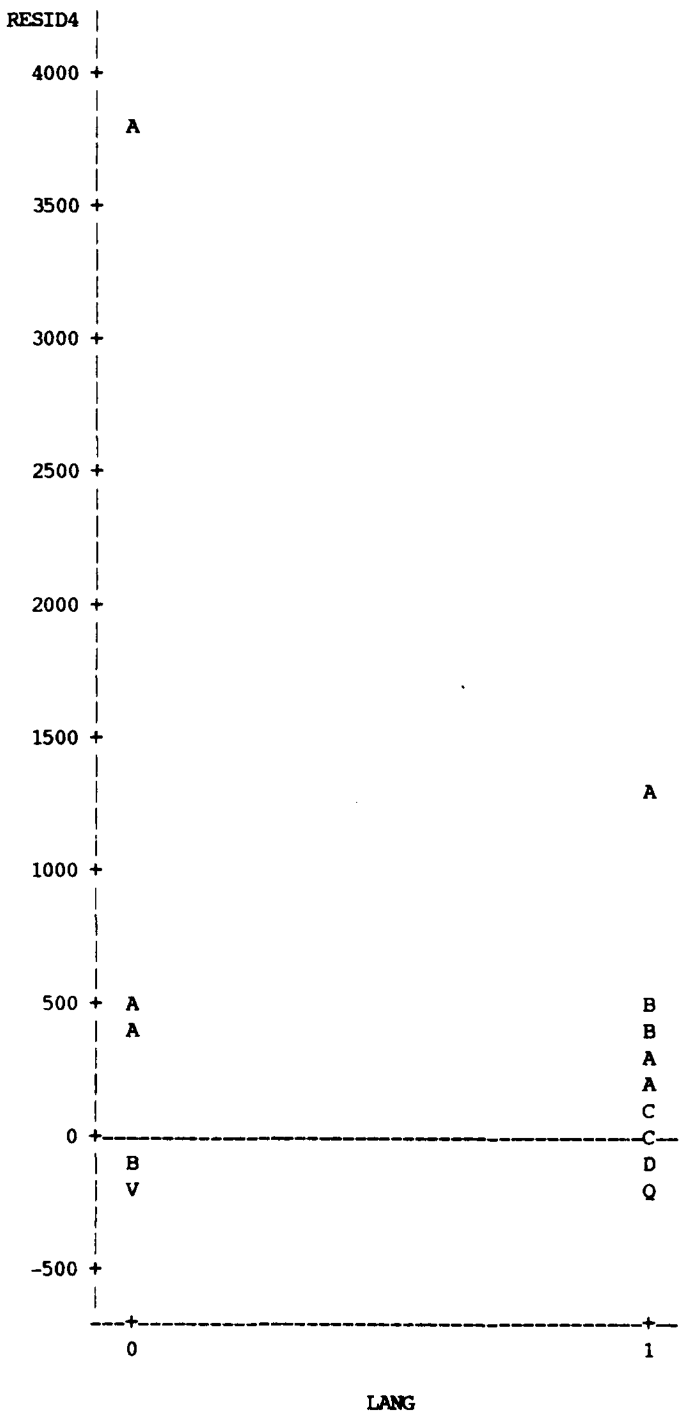


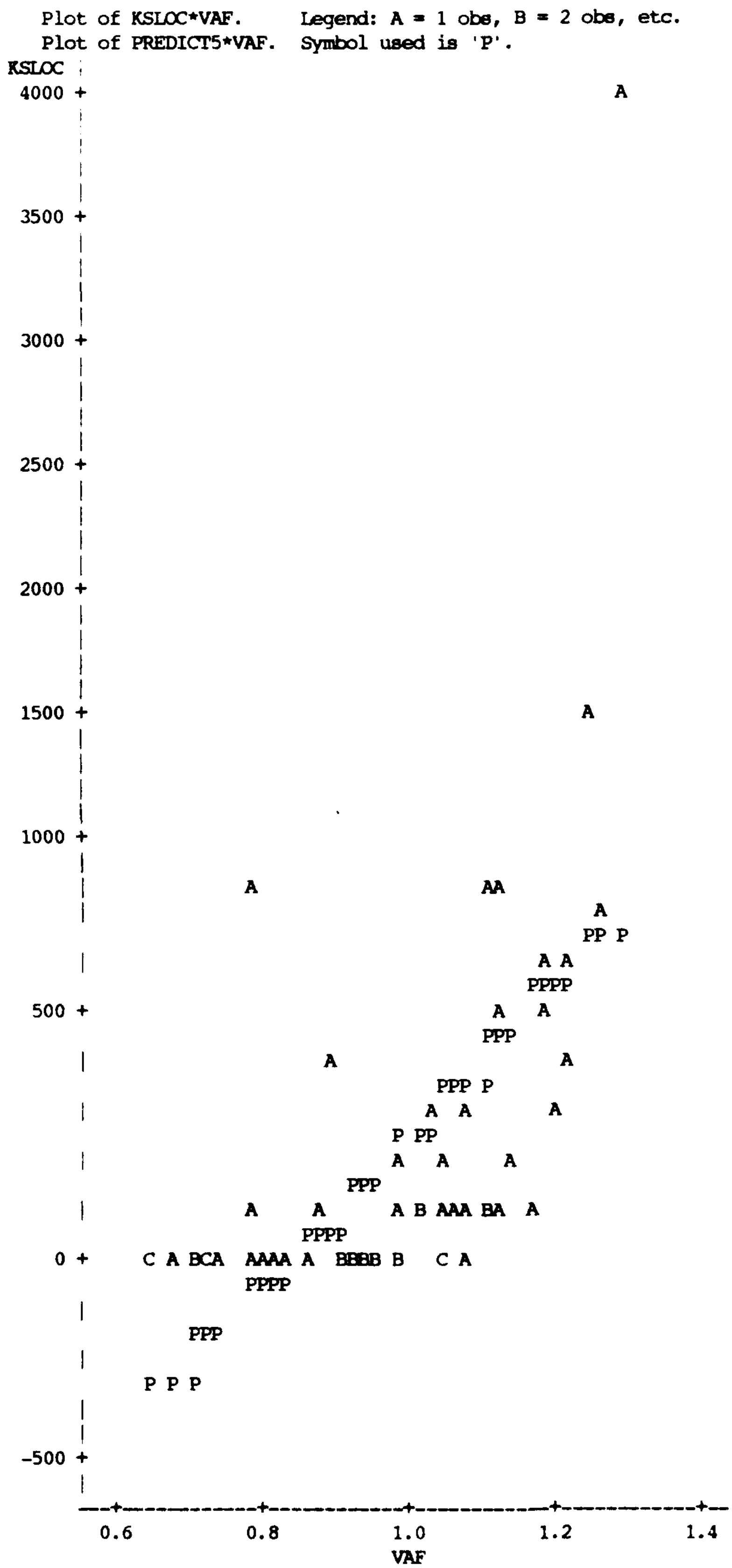
Plot of RESID3*EFP. Legend: A = 1 obs, B = 2 obs, etc.



```
    Plot of KSLOC*LANG.       Legend: A = 1 obs, B = 2 obs, etc.
    Plot of PREDICT4*FPSQRT.  Symbol used is 'P'.

  KSLOC |
4391.15 +
        |
        |
        |
        | A
3903.91 +
        |
        |
        |
        |
3416.66 +
        |
        |
        |
        |
2929.42 +
        |
        |
        |
        |
2442.17 +
        |
        |
        |
        |
1954.93 +
        |
        |
        |
        |
1467.68 + A
        |
        |
        |
        |
 980.44 +
        |
        | C
        | A
        | B
 493.19 + B
        | B
        | C
        | C
          PPPPPPPPP P  P      P                                  P
        | L
   5.95 + Z
        --+---------+---------+---------+---------+---------+---------+-
          0        100       200       300       400       500       600

                                       LANG
```

Plot of RESID4*LANG. Legend: A = 1 obs, B = 2 obs, etc.




Plot of KSLOC*VAF. Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT5*VAF. Symbol used is 'P'.
KSLOC
4000
3500
3000
2500
2000
1500
1000
500
0
-500
0.6
0.8
1.0
1.2
1.4
VAF

Plot of RESID5*VAF. Legend: A = 1 obs, B = 2 obs, etc.

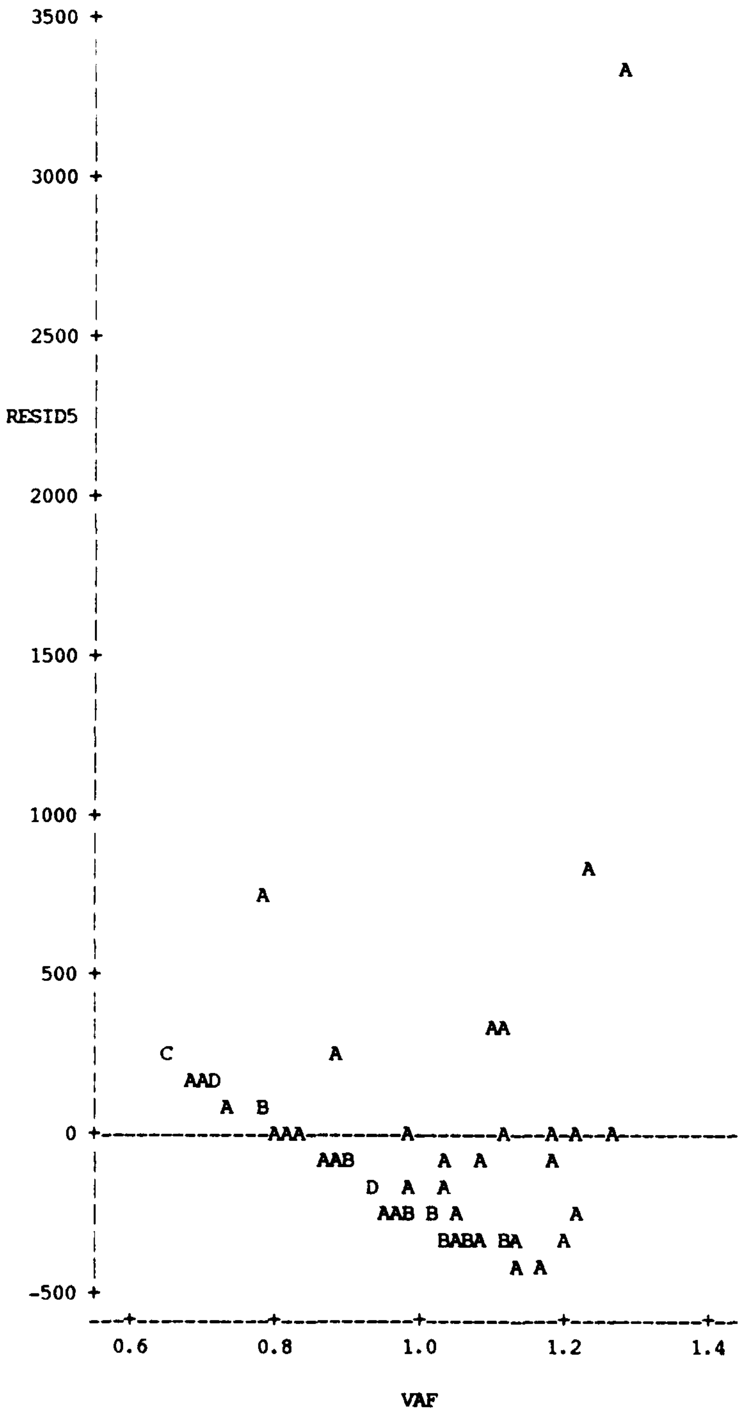
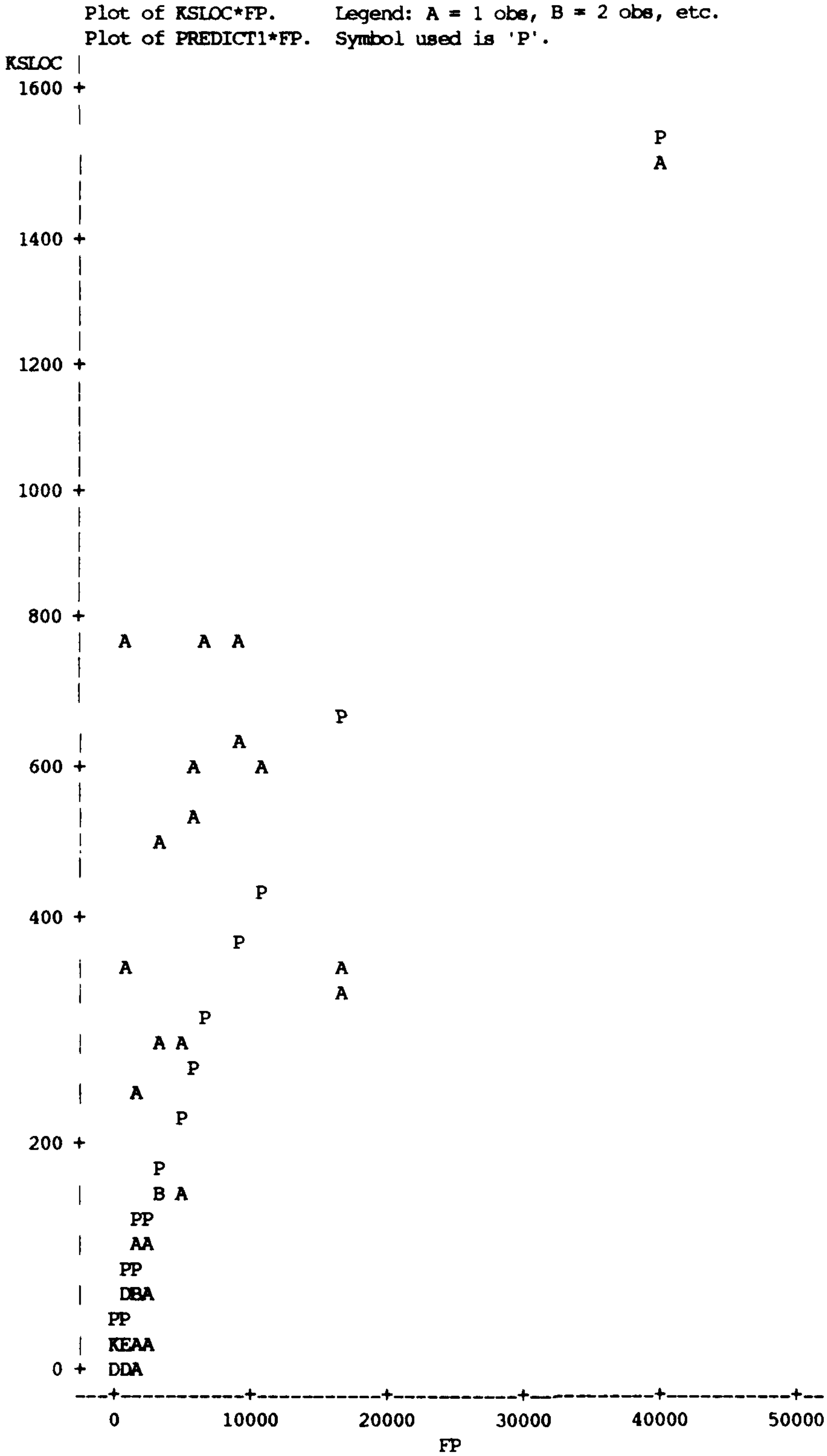
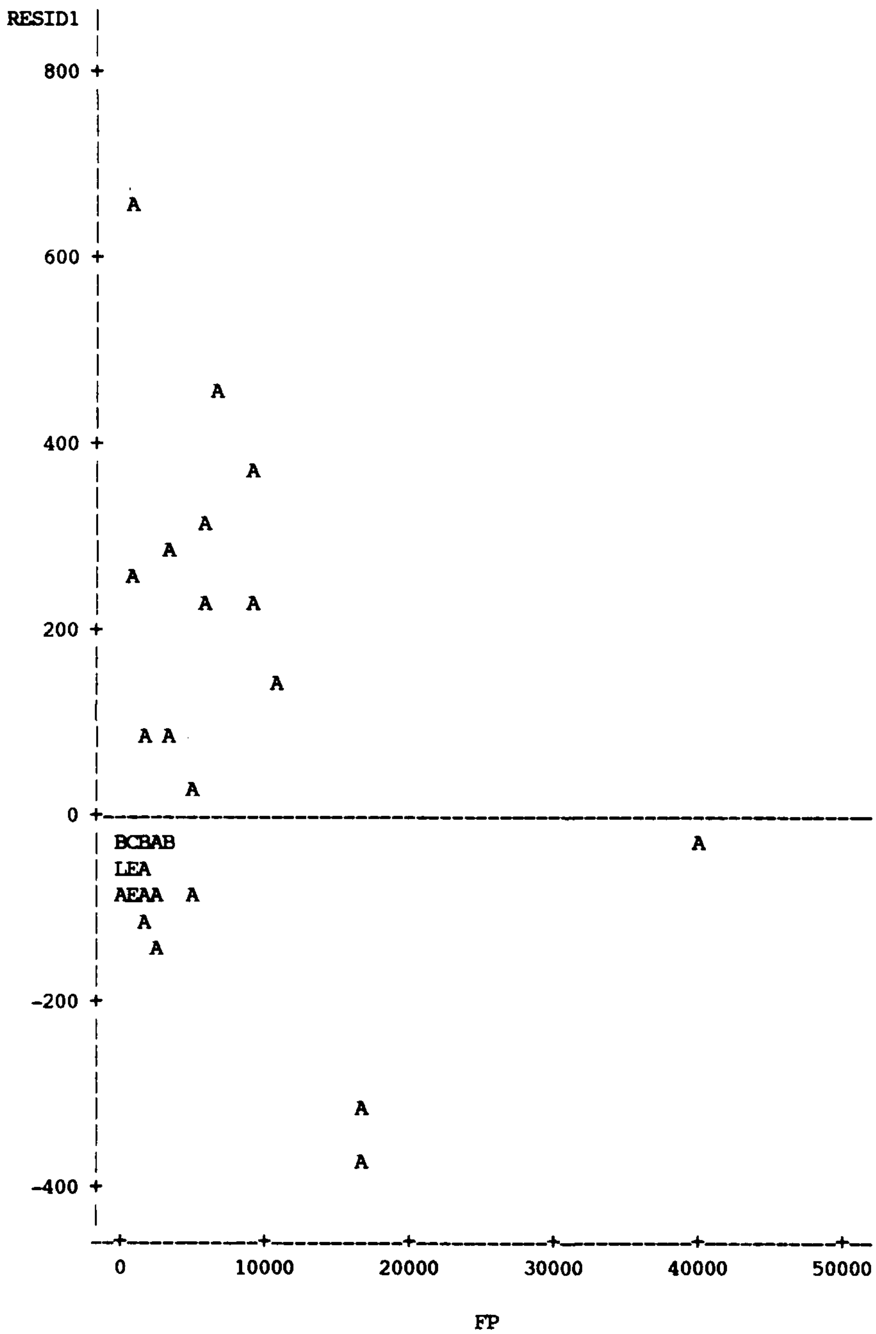


Table 16

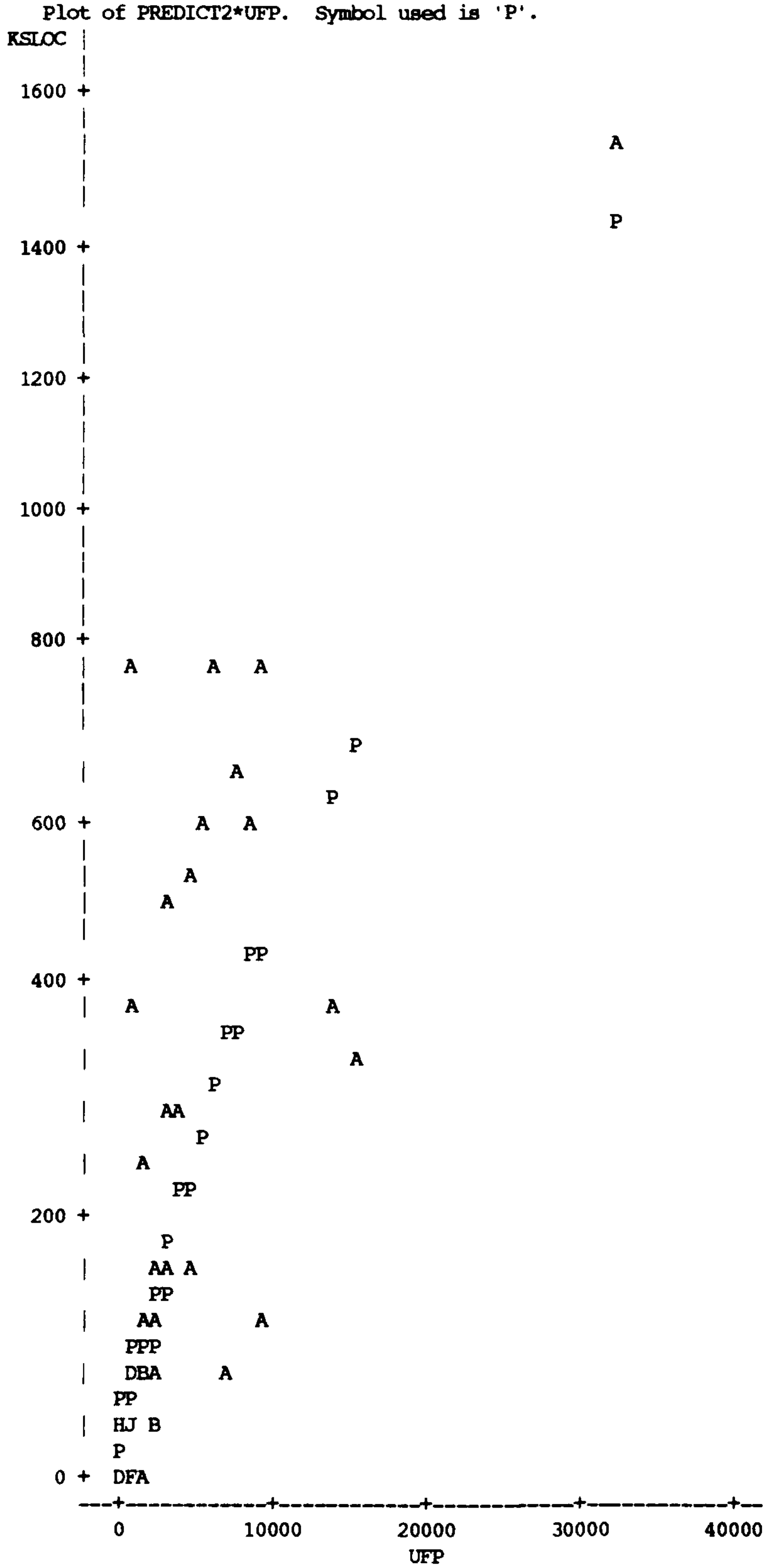
Transformation Analysis of SPDS Data with CAMS Removed



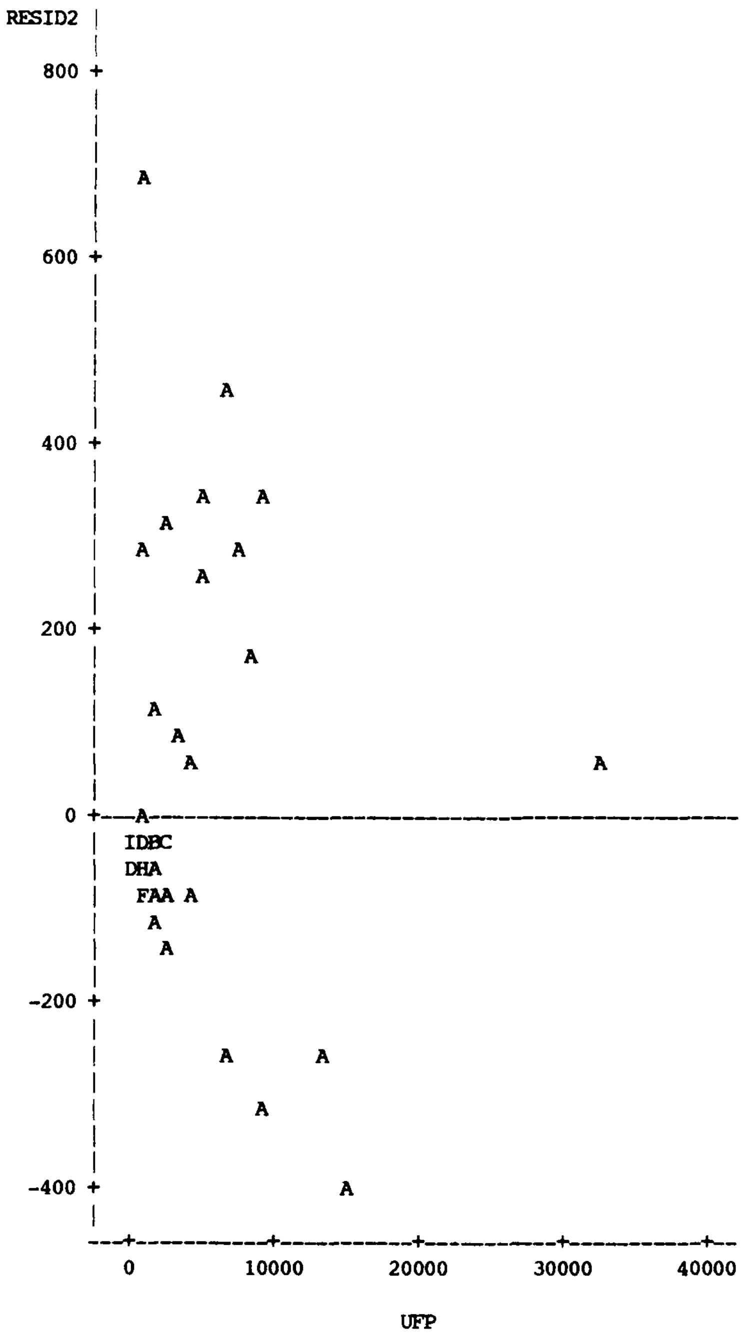
Plot of RESID1*FP. Legend: A = 1 obs, B = 2 obs, etc.



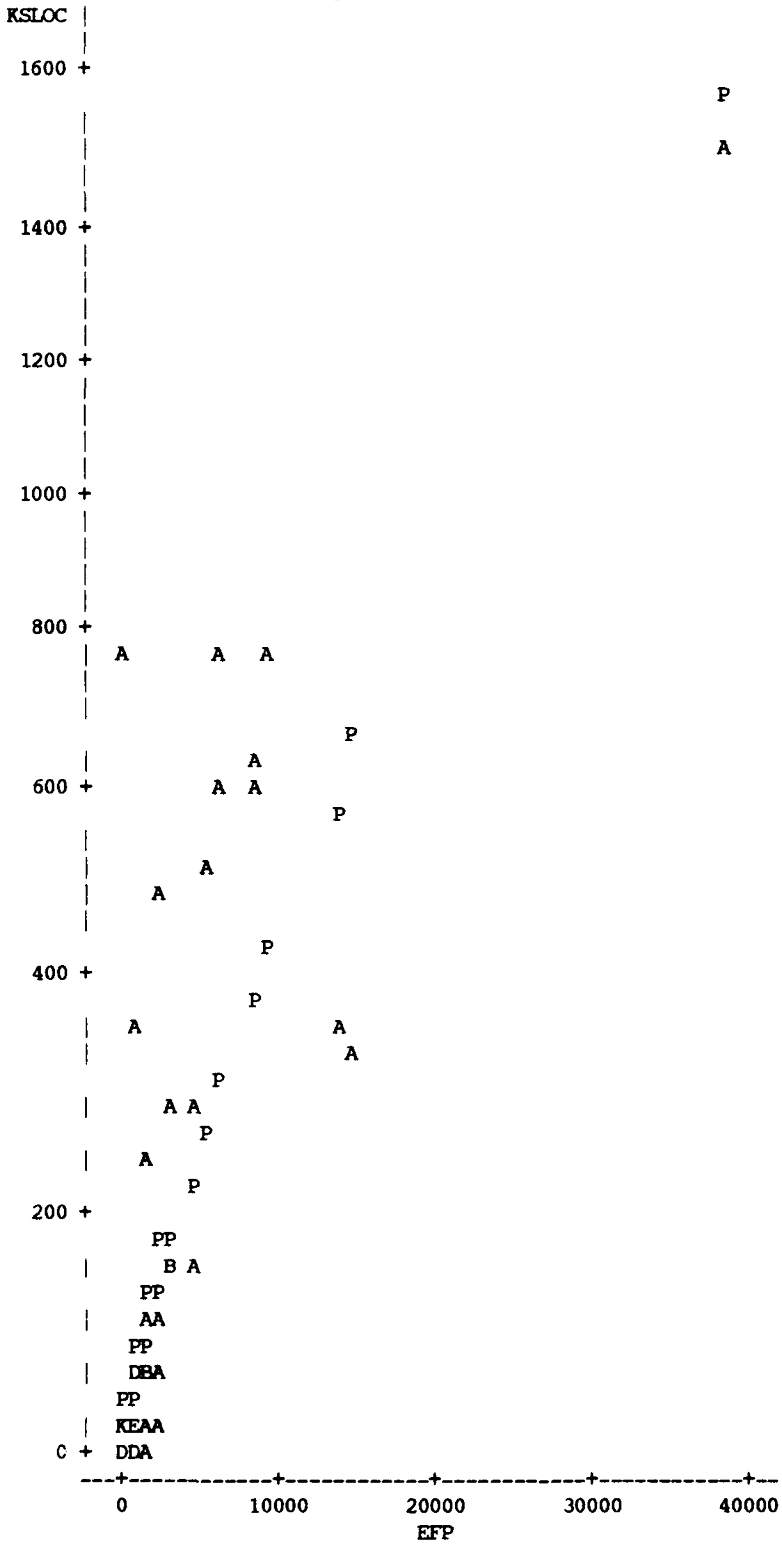
Plot of KSLOC*UFP.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT2*UFP. Symbol used is 'P'.



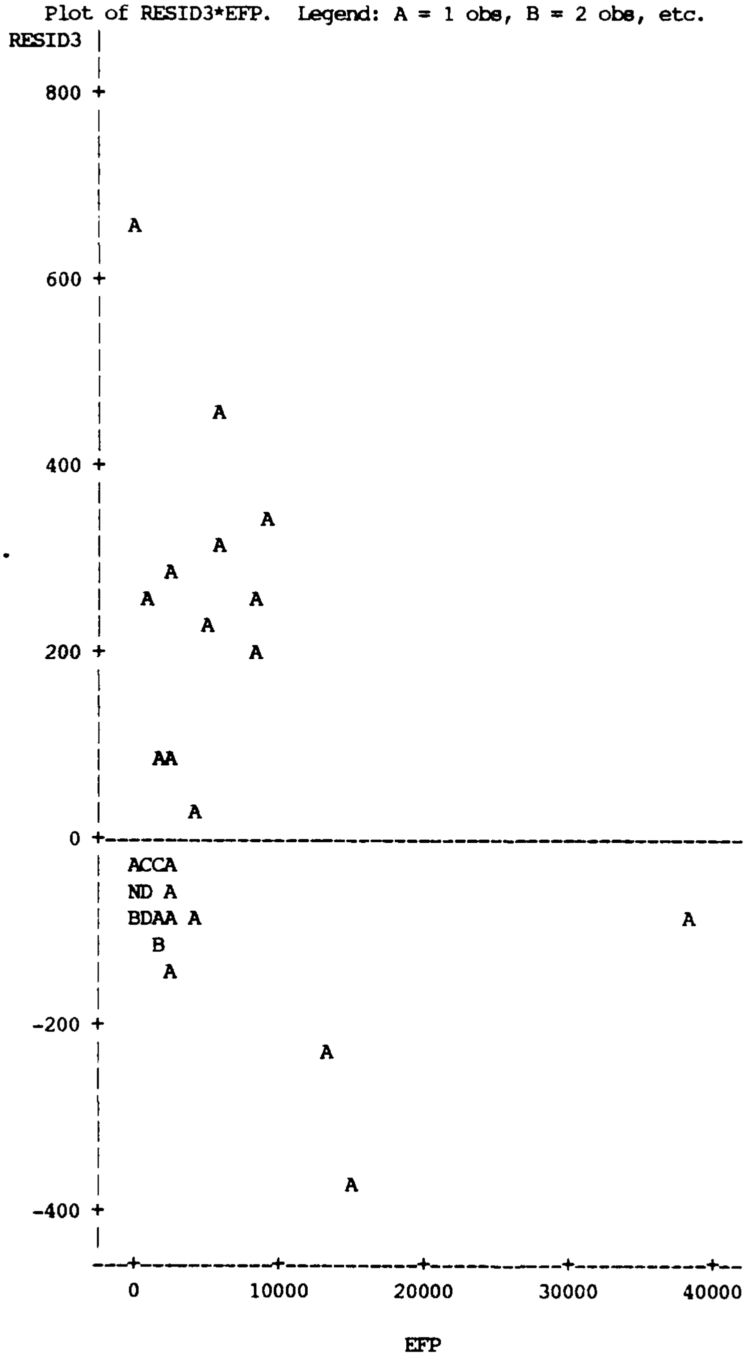
Plot of RESID2*UFP. Legend: A = 1 obs, B = 2 obs, etc.



Plot of KSLOC*EFP.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT3*EFP. Symbol used is 'P'.



Plot of RESID3*EFP. Legend: A = 1 obs, B = 2 obs, etc.

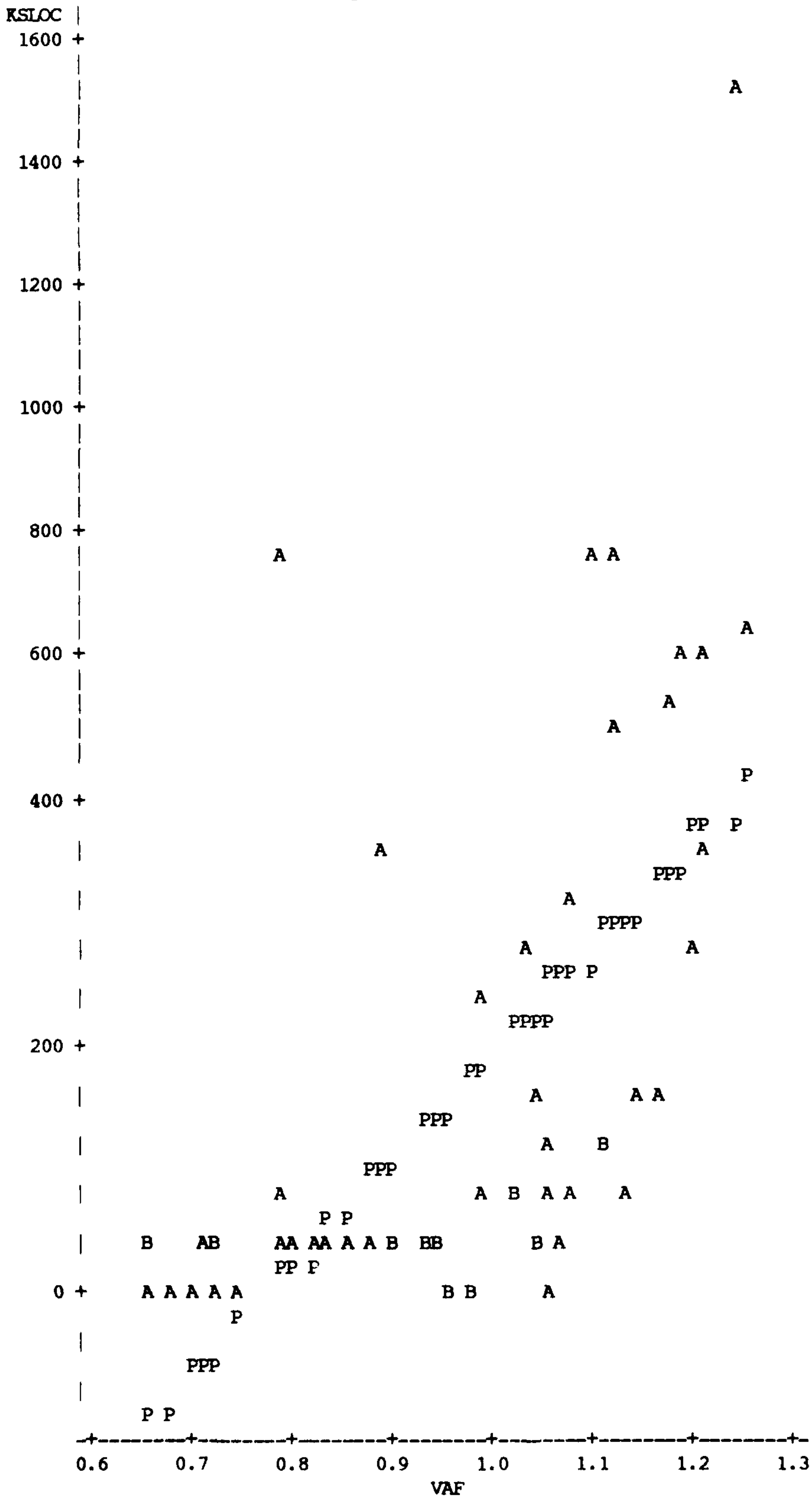


```
Plot of KSLOC*LANG.     Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT4*LANG.  Symbol used is 'P'.

    KSLOC |
          |
  1573.15 +
          |
          |                                            A
          |
  1416.43 +
          |
          |
          |
  1259.71 +
          |
          |
          |
  1102.99 +
          |
          |
          |
   946.27 +
          |
          |
          |
   789.55 +  A                                         A
          |                                            A
          |
          |                                            A
   632.83 +
          |  A                                         A
          |
          |                                            A
   476.11 +                                            A
          |
          |
          |                                            B
   319.39 +                                            A
          |                                            B
          |                                            A
                                                       P
          |
   162.67 +  A                                         B
          |  A                                         A
          |  C                                         E
             P
          |  I                                         G
     5.95 +  J                                         F
          |
          ---+-----------------------------------------+--
             0                                         1

                                  LANG
```

Plot of RESID4*LANG. Legend: A = 1 obs, B = 2 obs, etc.

```
RESID4 |
       |
  1400 +
       |
       |
       |
       |                                          A
  1200 +
       |
       |
       |
       |
  1000 +
       |
       |
       |
       |
   800 +
       |
       |
       |  A
       |
   600 +
       |
       |  A                                       B
       |
       |
   400 +                                          A
       |                                          A
       |
       |                                          A
       |                                          A
   200 +
       |
       |                                          B
       |
       |  B                                       B
     0 +--C---------------------------------------B--
       |  H
       |  K                                       B
       |                                          A
       |                                          E
  -200 +                                          G
       |                                          F
       |
       |
       |
  -400 +
       |
       ---+---------------------------------------+--
          0                                       1

                               LANG
```

Plot of KSLOC*VAF.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT5*VAF. Symbol used is 'P'.



Plot of RESID5*VAF. Legend: A = 1 obs, B = 2 obs, etc.

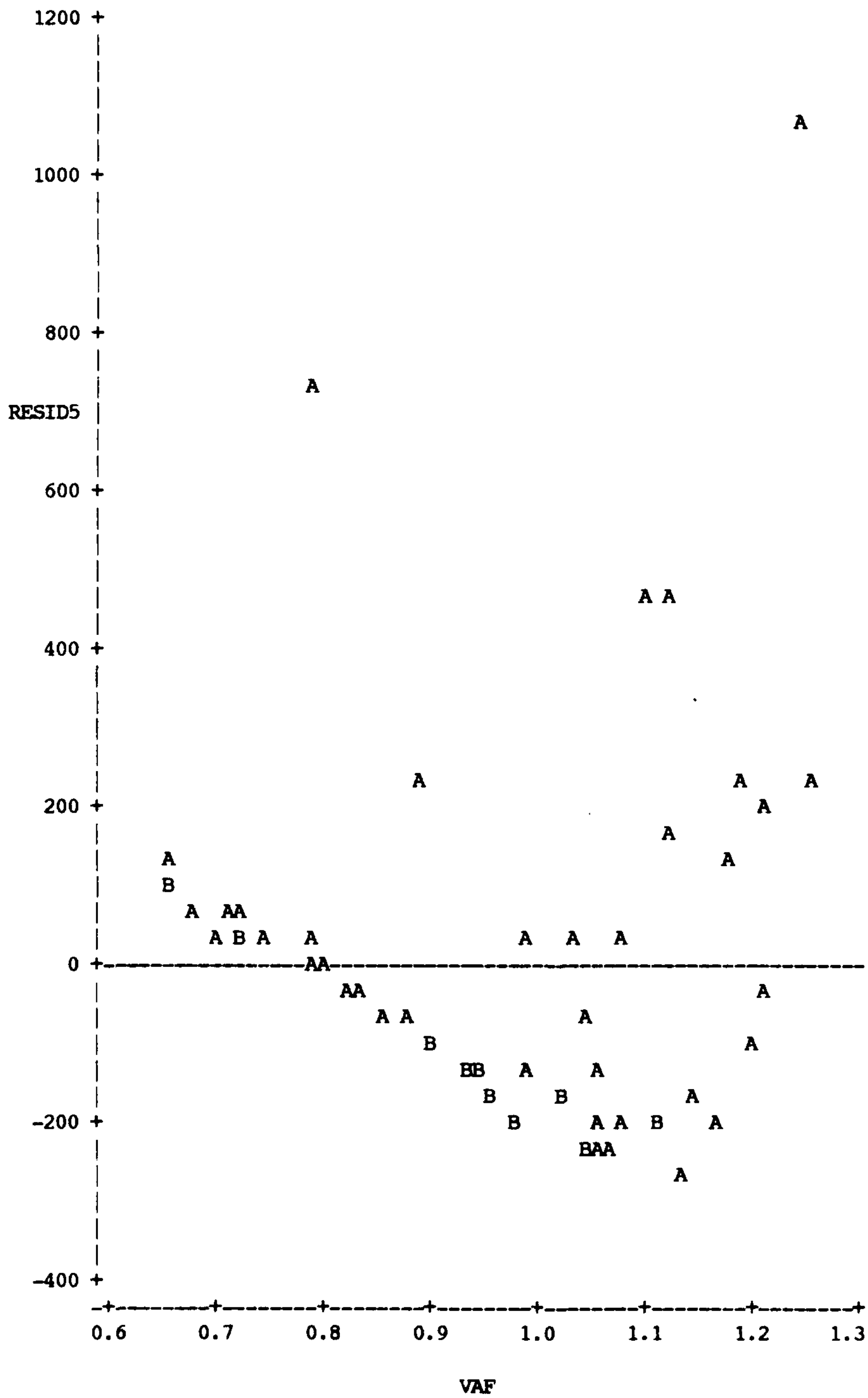
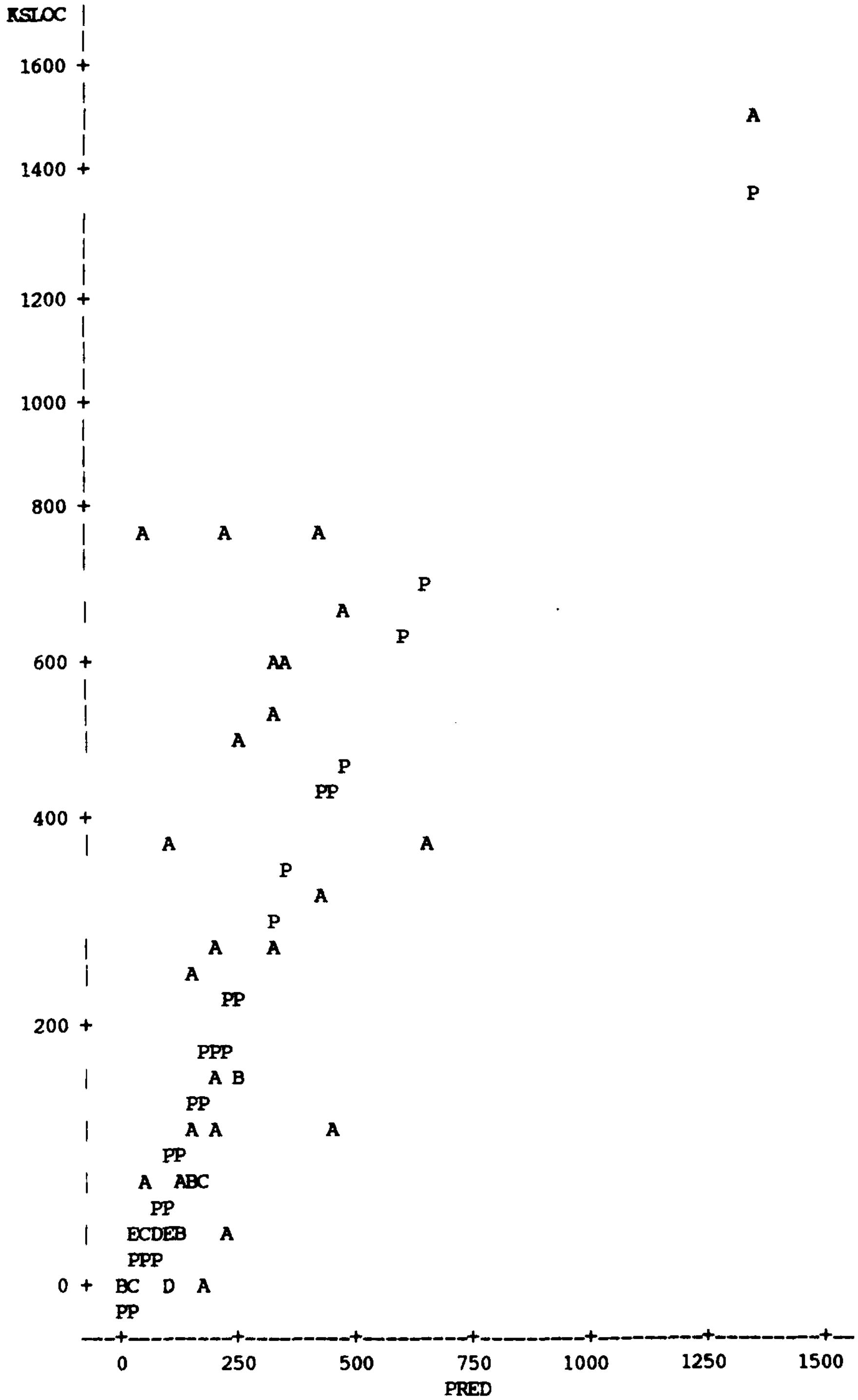


Table 17

Heteroscedasticity & Transformation Analysis of SPDS Data "Best" Model

```
Plot of KSLOC*PRED.     Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT1*PRED.  Symbol used is 'P'.
```



Plot of RESID1*PRED. Legend: A = 1 obs, B = 2 obs, etc.

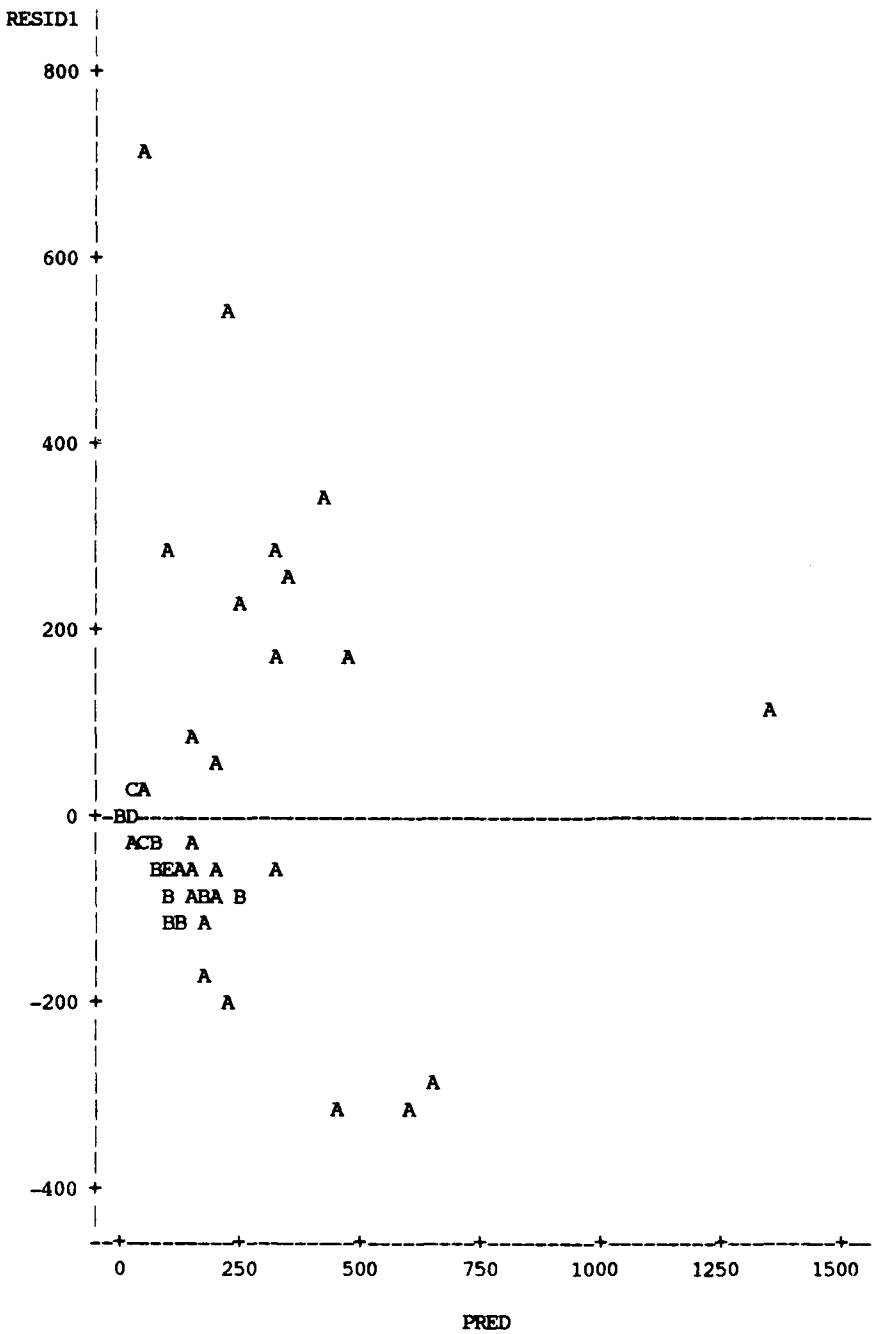
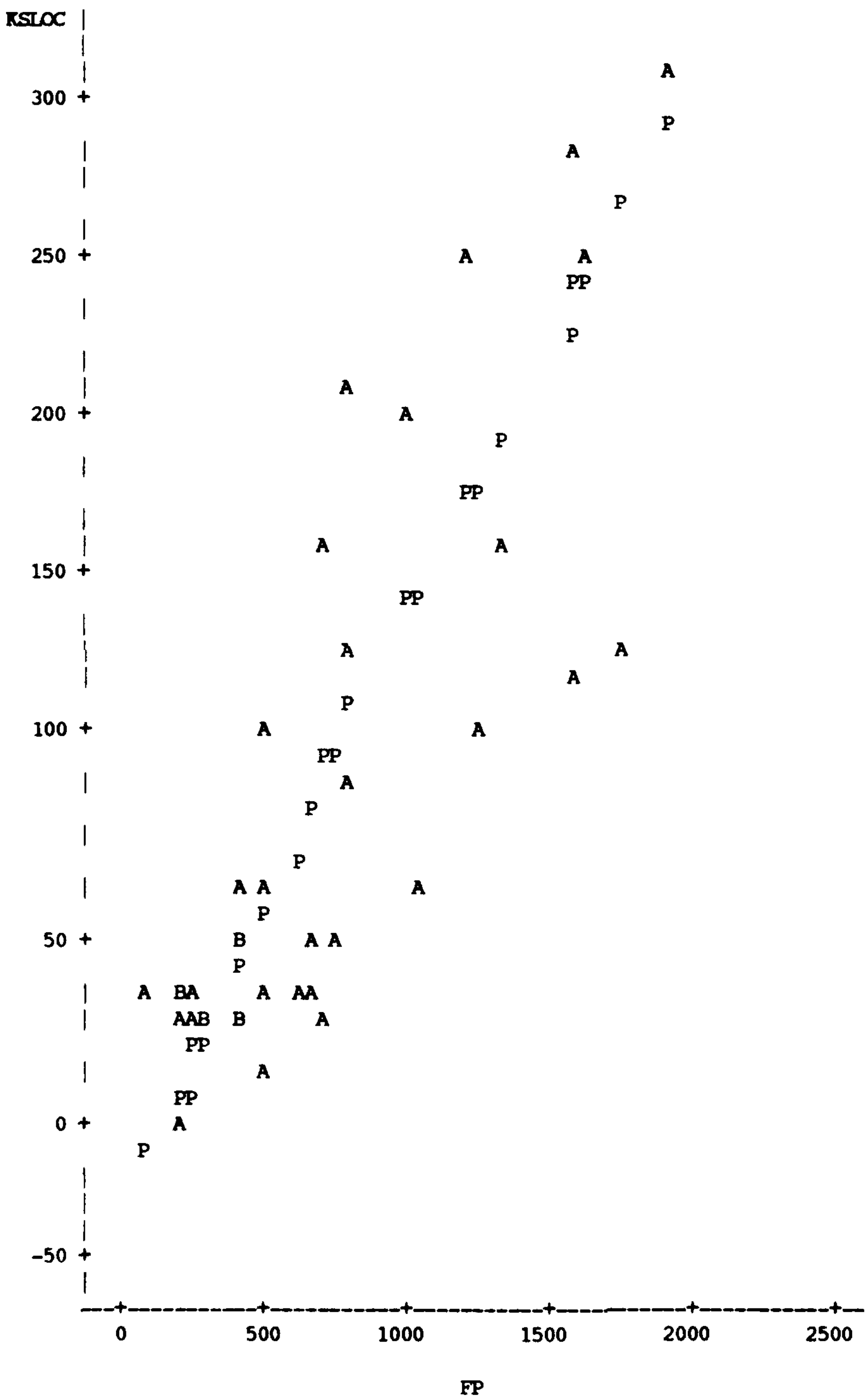


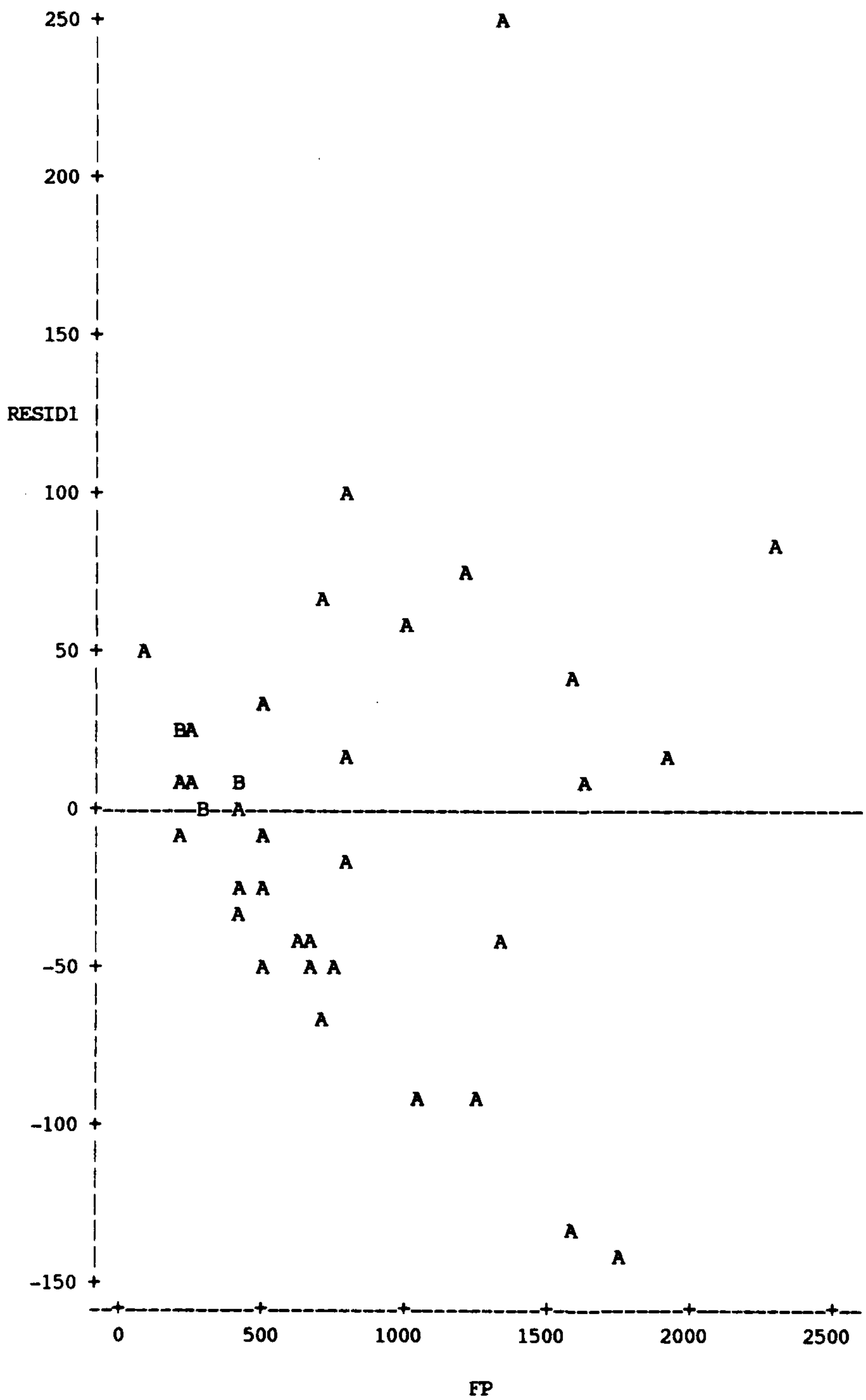
Table 18

Transformation Analysis of Commercial Data

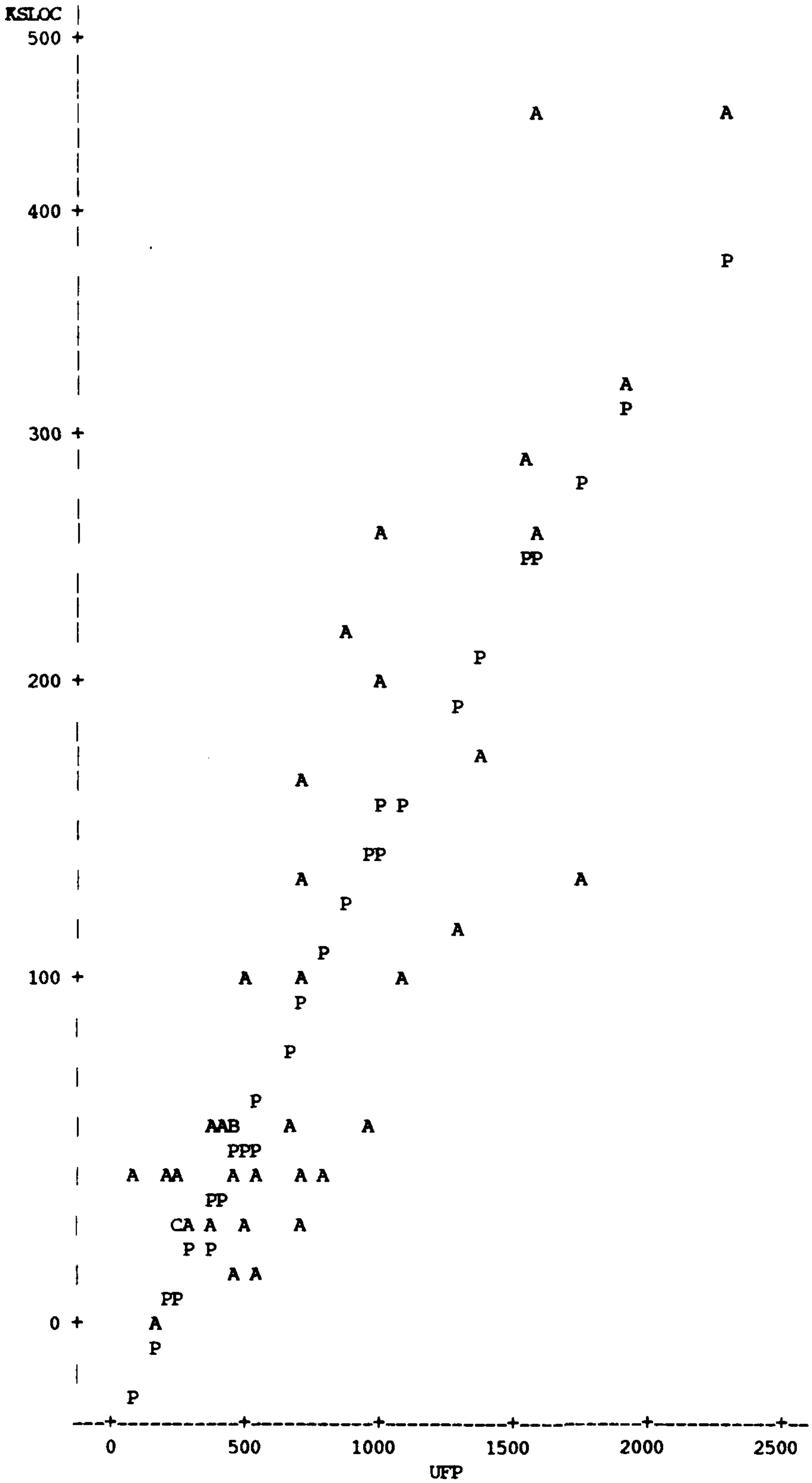
Plot of KSLOC*FP.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT2*FP. Symbol used is 'P'.



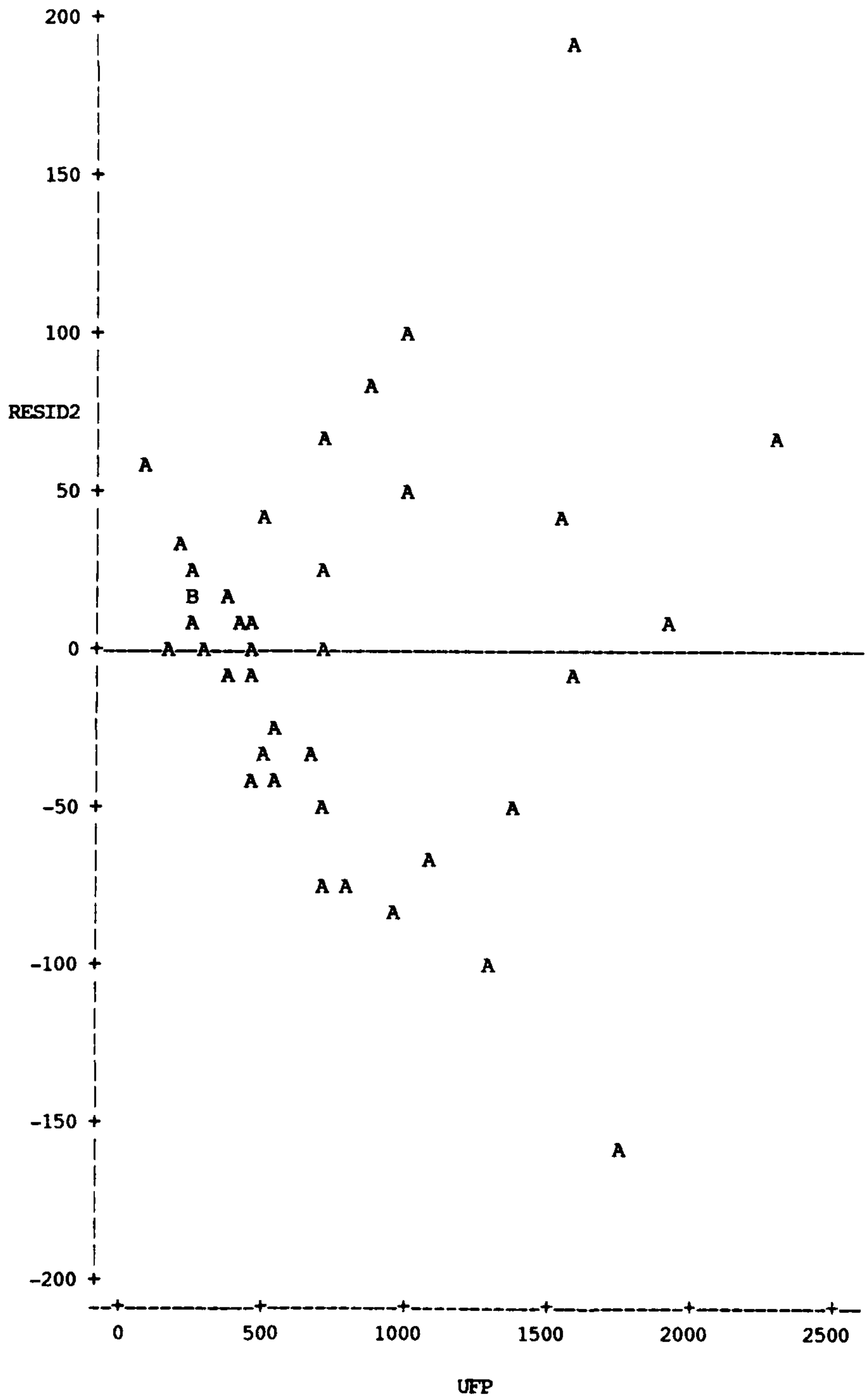
Plot of RESID1*FP. Legend: A = 1 obs, B = 2 obs, etc.



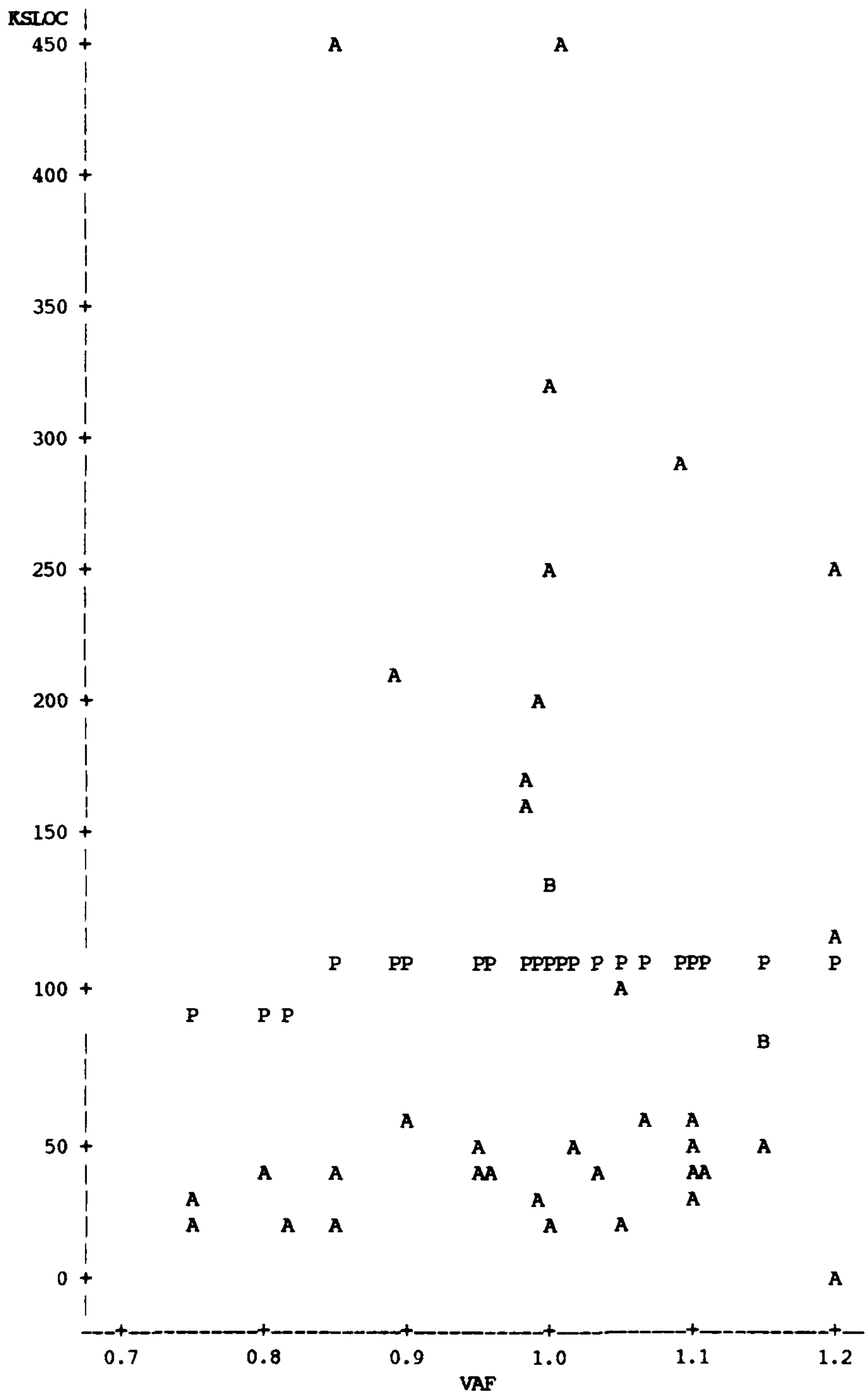
Plot of KSLOC*UFP.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT2*UFP. Symbol used is 'P'.



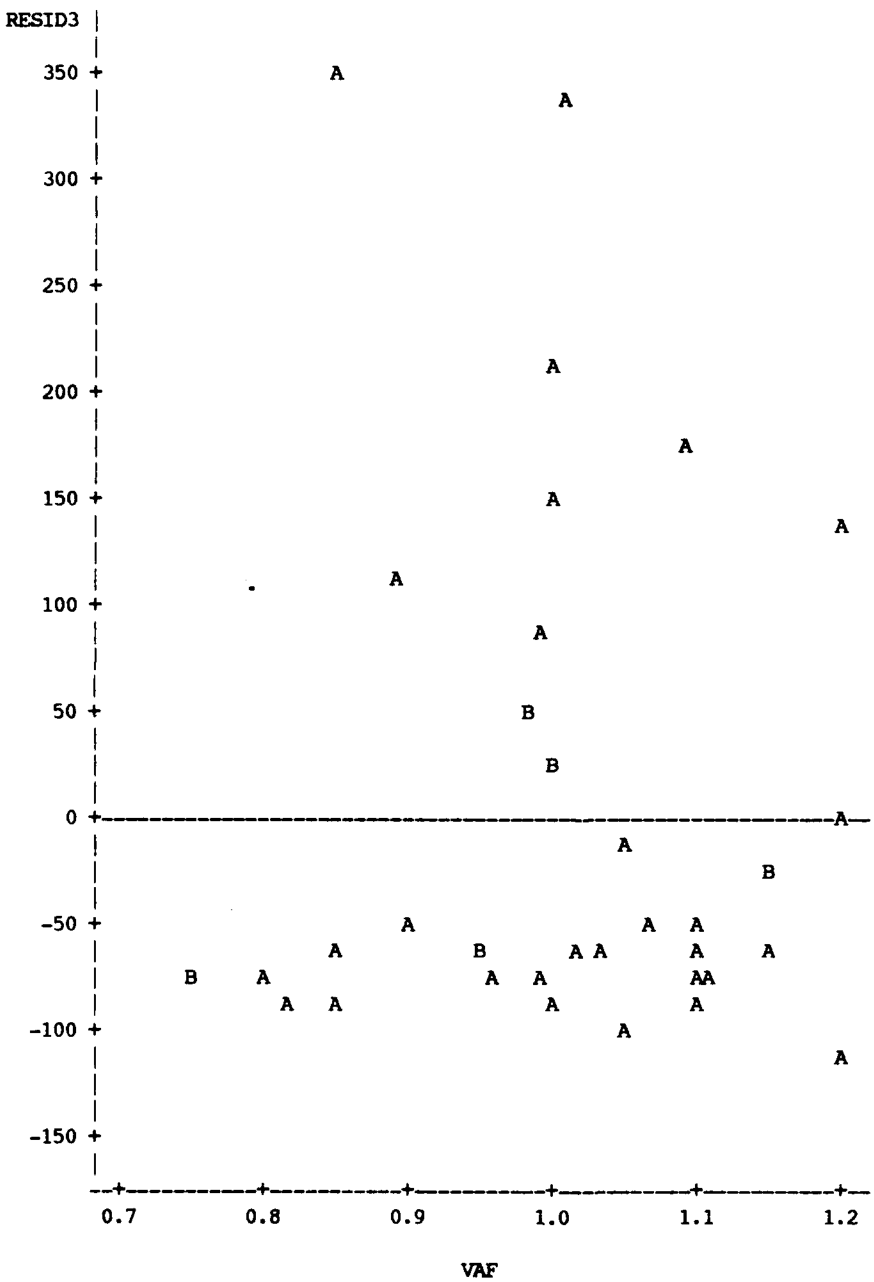
Plot of RESID2*UFP. Legend: A = 1 obs, B = 2 obs, etc.



Plot of KSLOC*VAF.   Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT3*VAF. Symbol used is 'P'.



Plot of RESID3*VAF. Legend: A = 1 obs, B = 2 obs, etc.



```
Plot of KSLOC*LANG.     Legend: A = 1 obs, B = 2 obs, etc.
Plot of PREDICT4*LANG.  Symbol used is 'P'.

  KSLOC |
        |
 467.10 +
        |
        |  B
        |
        |
        |
        |
 389.75 +
        |
        |
        |
        |
        |
        |  A
 312.40 +
        |
        |  A
        |
        |
        |  B
        |
 235.05 +
        |
        |  A
        |  A
        |
        |
        |  A
 157.70 +  A
        |
        |
        |  B
           P
        |                                           A
        |
        |  C
  80.35 +
        |
        |  B                                        B
        |  C                                        B
                                                    P
        |  D                                        A
        |  F                                        A
        |  A
   3.00 +                                           A
        |
        ---+----------------------------------------+--
           0                                        1

                               LANG
```

```
Plot of RESID4*LANG.  Legend: A = 1 obs, B = 2 obs, etc.

RESID4 |
       |
   350 +
       |
       |  B
       |
   300 +
       |
       |
       |
   250 +
       |
       |
       |
   200 +
       |  A
       |
       |  A
   150 +
       |
       |  B
       |
   100 +
       |  A
       |  A
       |                                           A
    50 +
       |  B
       |
       |                                           A
     0 +--B----------------------------------------C--
       |                                           A
       |  B                                        A
       |  A
   -50 +                                           A
       |  B
       |  B
       |  E
  -100 +  F
       |  A
       |
       |
  -150 +
       |
       ---+----------------------------------------+--
          0                                        1

                               LANG
```

Table 19

ANOVA Tables for Military Database, All SPDS Data, Straight Linear Regression

Model: MODEL A
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	16139532.952	16139532.952	314.682	0.0001
Error	53	2718282.9124	51288.356838		
C Total	54	18857815.865			

Root MSE	226.46933	R-square	0.8559
Dep Mean	261.83327	Adj R-sq	0.8531
C.V.	86.49372		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	144.865807	31.24087739	4.637	0.0001
FP	1	0.013617	0.00076760	17.739	0.0001

Model: MODEL B
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	16221200.298	16221200.298	326.071	0.0001
Error	53	2636615.5666	49747.463521		
C Total	54	18857815.865			

Root MSE	223.04139	R-square	0.8602
Dep Mean	261.83327	Adj R-sq	0.8575
C.V.	85.18451		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	138.318643	30.84292932	4.485	0.0001
UFP	1	0.017610	0.00097521	18.057	0.0001

Model: MODEL C
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	16322638.507	16322638.507	341.238	0.0001
Error	53	2535177.3576	47833.535049		
C Total	54	18857815.865			

Root MSE	218.70879	R-square	0.8656
Dep Mean	261.83327	Adj R-sq	0.8630
C.V.	83.52979		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	140.007216	30.21909910	4.633	0.0001
EFP	1	0.016809	0.00090994	18.473	0.0001

Model: MODEL D
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	16443384.48	8221692.2398	177.072	0.0001
Error	52	2414431.385	46431.372788		
C Total	54	18857815.865			

Root MSE	215.47940	R-square	0.8720
Dep Mean	261.83327	Adj R-sq	0.8670
C.V.	82.29642		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	64.361749	43.28867531	1.487	0.1431
FP	1	0.013804	0.00073402	18.806	0.0001
LANG	1	149.624751	58.48957852	2.558	0.0135

Model: MODEL E
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	17077850.18	5692616.7265	163.106	0.0001
Error	51	1779965.685	34901.287941		
C Total	54	18857815.865			

Root MSE	186.81886	R-square	0.9056
Dep Mean	261.83327	Adj R-sq	0.9001
C.V.	71.35031		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	69.496854	37.55024408	1.851	0.0700
FP	1	0.013403	0.00064332	20.833	0.0001
LANG	1	55.987004	55.26139900	1.013	0.3158
FPLANG	1	0.018734	0.00439381	4.264	0.0001

Model: MODEL F
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	16729493.273	8364746.6363	204.371	0.0001
Error	52	2128322.592	40929.280615		
C Total	54	18857815.865			

Root MSE	202.30986	R-square	0.8871
Dep Mean	261.83327	Adj R-sq	0.8828
C.V.	77.26667		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-475.445954	176.39796643	-2.695	0.0095
UFP	1	0.016471	0.00094171	17.491	0.0001
VAF	1	632.326825	179.43270652	3.524	0.0009

Model: MODEL G
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	16864889.345	5621629.7817	143.860	0.0001
Error	51	1992926.5197	39076.990581		
C Total	54	18857815.865			

Root MSE	197.67901	R-square	0.8943
Dep Mean	261.83327	Adj R-sq	0.8881
C.V.	75.49805		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-385.699734	178.97666180	-2.155	0.0359
UFP	1	0.151850	0.07273462	2.088	0.0418
VAF	1	492.568920	190.72569448	2.583	0.0127
UV	1	-0.104759	0.05627917	-1.861	0.0685

Model: MODEL H
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	16783704.776	5594568.2585	137.564	0.0001
Error	51	2074111.089	40668.844883		
C Total	54	18857815.865			

Root MSE	201.66518	R-square	0.8900
Dep Mean	261.83327	Adj R-sq	0.8835
C.V.	77.02046		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-408.589850	185.12534762	-2.207	0.0318
UFP	1	0.016778	0.00097553	17.199	0.0001
VAF	1	523.880813	202.02437936	2.593	0.0124
LANG	1	71.359744	61.80711578	1.155	0.2537

Model: MODEL I
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	17253038.343	5751012.7809	177.564	0.0001
Error	55	1781360.6112	32388.374748		
C Total	58	19034398.954			

Root MSE	179.96770	R-square	0.9064
Dep Mean	247.39746	Adj R-sq	0.9013
C.V.	72.74436		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-210.491063	149.63471375	-1.407	0.1651
VAF	1	320.403524	158.92487137	2.016	0.0487
UV	1	0.012931	0.00064509	20.045	0.0001
ULV	1	0.015897	0.00424572	3.744	0.0004

Variable	DF	Tolerance	Variance Inflation
INTERCEP	1	.	0.00000000
VAF	1	0.72156960	1.38586770
UV	1	0.89219717	1.12082848
ULV	1	0.79848370	1.25237372

Collinearity Diagnostics(intercept adjusted)

Number	Eigenvalue	Condition Number	Var Prop VAF	Var Prop UV	Var Prop ULV
1	1.60158	1.00000	0.2056	0.1175	0.1659
2	0.90605	1.32953	0.0028	0.6515	0.2952
3	0.49237	1.80355	0.7916	0.2310	0.5389

Table 20

ANOVA Tables for Military Database, CAMS Removed, Straight Linear Regression

Model: MODEL A
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	2822834.8096	2822834.8096	92.445	0.0001
Error	52	1587842.039	30535.423826		
C Total	53	4410676.8486			

Root MSE	174.74388	R-square	0.6400
Dep Mean	192.08833	Adj R-sq	0.6331
C.V.	90.97059		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	74.323970	26.74864132	2.779	0.0076
FP	1	0.036310	0.00377649	9.615	0.0001

Model: MODEL B
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	2822360.5207	2822360.5207	92.401	0.0001
Error	52	1588316.3279	30544.544767		
C Total	53	4410676.8486			

Root MSE	174.76998	R-square	0.6399
Dep Mean	192.08833	Adj R-sq	0.6330
C.V.	90.98417		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	65.182325	27.20174558	2.396	0.0202
UFP	1	0.044129	0.00459073	9.613	0.0001

Model: MODEL C
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	2834968.8878	2834968.8878	93.557	0.0001
Error	52	1575707.9607	30302.076168		
C Total	53	4410676.8486			

Root MSE	174.07492	R-square	0.6428
Dep Mean	192.08833	Adj R-sq	0.6359
C.V.	90.62233		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	77.766863	26.47346186	2.938	0.0049
EFP	1	0.039314	0.00406457	9.672	0.0001

Model: MODEL D
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	2887843.8665	1443921.9333	48.357	0.0001
Error	51	1522832.982	29859.470236		
C Total	53	4410676.8486			

Root MSE	172.79893	R-square	0.6547
Dep Mean	192.08833	Adj R-sq	0.6412
C.V.	89.95806		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	40.533097	34.98720905	1.159	0.2521
FP	1	0.034759	0.00387965	8.959	0.0001
LANG	1	72.290289	48.99300521	1.476	0.1462

Model: MODEL E
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	3072689.7391	1024229.913	38.275	0.0001
Error	50	1337987.1095	26759.742189		
C Total	53	4410676.8486			

Root MSE	163.58405	R-square	0.6966
Dep Mean	192.08833	Adj R-sq	0.6784
C.V.	85.16085		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-9.399213	38.18337594	-0.246	0.8066
FP	1	0.070290	0.01400896	5.017	0.0001
LANG	1	134.883071	52.13747478	2.587	0.0126
FPLANG	1	-0.038153	0.01451674	-2.628	0.0114

Model: MODEL F
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	2869692.4529	1434846.2264	47.487	0.0001
Error	51	1540984.3957	30215.380308		
C Total	53	4410676.8486			

Root MSE	173.82572	R-square	0.6506
Dep Mean	192.08833	Adj R-sq	0.6369
C.V.	90.49260		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-143.857924	169.19642296	-0.850	0.3992
UFP	1	0.040347	0.00547535	7.369	0.0001
VAF	1	224.957782	179.73718583	1.252	0.2164

Model: MODEL G
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	2912719.9186	970906.63955	32.408	0.0001
Error	50	1497956.9299	29959.138598		
C Total	53	4410676.8486			

Root MSE	173.08708	R-square	0.6604
Dep Mean	192.08833	Adj R-sq	0.6400
C.V.	90.10807		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-129.782693	168.88634006	-0.768	0.4458
UFP	1	-0.057615	0.08192434	-0.703	0.4851
VAF	1	230.315261	179.02925564	1.286	0.2042
UV	1	0.080428	0.06711218	1.198	0.2364

Model: MODEL H
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	2901215.9484	967071.9828	32.034	0.0001
Error	50	1509460.9001	30189.218003		
C Total	53	4410676.8486			

Root MSE	173.75045	R-square	0.6578
Dep Mean	192.08833	Adj R-sq	0.6372
C.V.	90.45341		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-98.344593	174.88975911	-0.562	0.5764
UFP	1	0.040177	0.00547548	7.338	0.0001
VAF	1	148.926222	194.45719690	0.766	0.4474
LANG	1	54.560347	53.39318978	1.022	0.3118

Model: MODEL I
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	3119949.4128	1039983.1376	40.287	0.0001
Error	50	1290727.4358	25814.548715		
C Total	53	4410676.8486			

Root MSE	160.66907	R-square	0.7074
Dep Mean	192.08833	Adj R-sq	0.6898
C.V.	83.64332		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-12.282559	37.45206700	-0.328	0.7443
LANG	1	136.473585	51.07967882	2.672	0.0102
FPLANG	1	-0.039795	0.01411536	-2.819	0.0069
UV	1	0.071800	0.01358643	5.285	0.0001

Variable	DF	Tolerance	Variance Inflation
INTERCEP	1	.	0.00000000
LANG	1	0.73692616	1.35698806
FPLANG	1	0.05997298	16.67417485
UV	1	0.06495952	15.39420320

Collinearity Diagnostics(intercept adjusted)

Number	Eigenvalue	Condition Number	Var Prop LANG	Var Prop FPLANG	Var Prop UV
1	2.14736	1.00000	0.0479	0.0124	0.0126
2	0.82114	1.61713	0.7650	0.0029	0.0085
3	0.03150	8.25598	0.1871	0.9847	C.9788

Model I is the "best" available model in this category with collinearity mitigated using the condition number < 10 standard.

Table 21

ANOVA Tables for Military Database, CAMS Removed, VAF & KSLOC Transformed

Model: MODEL A
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	41.20743	41.20743	29.182	0.0001
Error	52	73.42918	1.41210		
C Total	53	114.63660			

Root MSE	1.18832	R-square	0.3595
Dep Mean	4.25703	Adj R-sq	0.3471
C.V.	27.91425		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.807086	0.18189988	20.930	0.0001
FP	1	0.000139	0.00002568	5.402	0.0001

Model: MODEL B
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	42.89198	42.89198	31.088	0.0001
Error	52	71.74463	1.37970		
C Total	53	114.63660			

Root MSE	1.17461	R-square	0.3742
Dep Mean	4.25703	Adj R-sq	0.3621
C.V.	27.59220		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.762305	0.18281969	20.579	0.0001
UFP	1	0.000172	0.00003085	5.576	0.0001

Model: MODEL C
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	39.77235	39.77235	27.626	0.0001
Error	52	74.86425	1.43970		
C Total	53	114.63660			

Root MSE	1.19987	R-square	0.3469
Dep Mean	4.25703	Adj R-sq	0.3344
C.V.	28.18570		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.828832	0.18247783	20.982	0.0001
EFP	1	0.000147	0.00002802	5.256	0.0001

Model: MODEL D
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	54.36207	27.18103	22.999	0.0001
Error	51	60.27454	1.18185		
C Total	53	114.63660			

Root MSE	1.08713	R-square	0.4742
Dep Mean	4.25703	Adj R-sq	0.4536
C.V.	25.53731		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.326410	0.22011523	15.112	0.0001
FP	1	0.000117	0.00002441	4.780	0.0001
LANG	1	1.028330	0.30822998	3.336	0.0016

Model: MODEL E
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	68.54853	22.84951	24.789	0.0001
Error	50	46.08808	0.92176		
C Total	53	114.63660			

Root MSE	0.96008	R-square	0.5980
Dep Mean	4.25703	Adj R-sq	0.5738
C.V.	22.55291		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	2.888975	0.22410042	12.891	0.0001
FP	1	0.000428	0.00008222	5.205	0.0001
LANG	1	1.576678	0.30599782	5.153	0.0001
FPLANG	1	-0.000334	0.00008520	-3.923	0.0003

Model: MODEL F
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	58.81104	29.40552	26.864	0.0001
Error	51	55.82557	1.09462		
C Total	53	114.63660			

Root MSE	1.04624	R-square	0.5130
Dep Mean	4.25703	Adj R-sq	0.4939
C.V.	24.57677		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-0.071337	1.01837709	-0.070	0.9444
UFP	1	0.000103	0.00003296	3.115	0.0030
VAF	1	4.125557	1.08182094	3.814	0.0004

Model: MODEL G
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	59.59996	29.79998	27.614	0.0001
Error	51	55.03665	1.07915		
C Total	53	114.63660			

Root MSE	1.03882	R-square	0.5199
Dep Mean	4.25703	Adj R-sq	0.5011
C.V.	24.40249		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	1.780607	0.52895277	3.366	0.0015
UFP	1	0.000095250	0.00003355	2.839	0.0065
VAFSQD	1	2.246087	0.57082837	3.935	0.0003

Model: MODEL H
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	57.92892	28.96446	26.049	0.0001
Error	51	56.70768	1.11192		
C Total	53	114.63660			

Root MSE	1.05447	R-square	0.5053
Dep Mean	4.25703	Adj R-sq	0.4859
C.V.	24.77018		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	4.074269	0.18474963	22.053	0.0001
UFP	1	0.000110	0.00003242	3.396	0.0013
LNVAF	1	3.679235	1.00049189	3.677	0.0006

Model: MODEL I
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	61.92383	20.64128	19.579	0.0001
Error	50	52.71277	1.05426		
C Total	53	114.63660			

Root MSE	1.02677	R-square	0.5402
Dep Mean	4.25703	Adj R-sq	0.5126
C.V.	24.11938		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	1.657901	0.52930836	3.132	0.0029
UFP	1	0.000475	0.00025771	1.842	0.0714
VAFSQD	1	2.233479	0.56426975	3.958	0.0002
UVSQD	1	-0.000256	0.00017231	-1.485	0.1439

Model: MODEL J
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	64.48716	21.49572	21.432	0.0001
Error	50	50.14945	1.00299		
C Total	53	114.63660			

Root MSE	1.00149	R-square	0.5625
Dep Mean	4.25703	Adj R-sq	0.5363
C.V.	23.52564		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	1.895277	0.51258497	3.697	0.0005
UFP	1	0.000093833	0.00003235	2.901	0.0055
VAFSQD	1	1.763427	0.59216424	2.978	0.0045
LANG	1	0.675375	0.30595903	2.207	0.0319

Model: MODEL K
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	75.07075	18.76769	22.242	0.0001
Error	53	44.72097	0.84379		
C Total	57	119.79172			

Root MSE	0.91858	R-square	0.6267
Dep Mean	4.20538	Adj R-sq	0.5985
C.V.	21.84300		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	2.079403	0.41882736	4.965	0.0001
UFP	1	0.000374	0.00010024	3.730	0.0005
VAFLANG	1	1.070811	C.31478651	3.402	0.0013
ULVSQD	1	-0.000197	0.00006600	-2.982	0.0043
VAFSQD	1	1.077551	0.54289885	1.985	0.0524

Variable	DF	Tolerance	Variance Inflation
INTERCEP	1	.	0.00000000
UFP	1	0.05587852	17.89596327
VAFLANG	1	0.55186160	1.81204853
ULVSQD	1	0.05847874	17.10023088
VAFSQD	1	0.47968440	2.08470403

Collinearity Diagnostics(intercept adjusted)

Number	Eigenvalue	Condition Number	Var Prop UFP	Var Prop VAFLANG	Var Prop ULVSQD	Var Prop VAFSQD
1	2.71484	1.00000	0.0063	0.0333	0.0067	0.0387
2	0.77041	1.87720	0.0139	0.3893	0.0113	0.0721
3	0.48631	2.36273	0.0001	0.3167	0.0083	0.6419
4	0.02843	9.77148	0.9796	0.2606	0.9738	0.2473

Table 22

ANOVA Table for Military Database. All Data. Transformed DV into Ln of KSLOC

Model: MODEL A
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	76.09626	25.36542	23.180	0.0001
Error	55	60.18556	1.09428		
C Total	58	136.28183			

Root MSE	1.04608	R-square	0.5584
Dep Mean	4.27480	Adj R-sq	0.5343
C.V.	24.47085		

Parameter Estimates

Variable	DF	Estimate	Error	Parameter=0	Prob > |T|
INTERCEP	1	-0.105559	0.86976634	-0.121	0.9038
VAF	1	4.278940	0.92376629	4.632	0.0001
UV	1	0.000009950	0.00000375	2.654	0.0104
ULV	1	0.000059622	0.00002468	2.416	0.0190

Table 23

ANOVA Tables for Commercial Database, All Commercial Data Included, Straight Linear Regression

Model: MODEL A
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	326482.84028	326482.84028	69.339	0.0001
Error	37	174214.13408	4708.49011		
C Total	38	500696.97436			

Root MSE	68.61844	R-square	0.6521
Dep Mean	109.35897	Adj R-sq	0.6427
C.V.	62.74605		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-22.619786	19.28564643	-1.173	0.2483
FP	1	0.168594	0.02024662	8.327	0.0001

Model: MODEL B
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	356026.12609	356026.12609	91.055	0.0001
Error	37	144670.84827	3910.02293		
C Total	38	500696.97436			

Root MSE	62.53018	R-square	0.7111
Dep Mean	109.35897	Adj R-sq	0.7033
C.V.	57.17882		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-30.398752	17.74169554	-1.713	0.0950
UFP	1	0.180566	0.01892272	9.542	0.0001

Model: MODEL C
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	357480.62254	178740.31127	44.930	0.0001
Error	36	143216.35182	3978.23200		
C Total	38	500696.97436			

Root MSE	63.07323	R-square	0.7140
Dep Mean	109.35897	Adj R-sq	0.6981
C.V.	57.67540		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-6.930423	18.59684424	-0.373	0.7116
FP	1	0.166857	0.01862084	8.961	0.0001
LANG	1	-69.857710	25.02615257	-2.791	0.0083

Model: MODEL D
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	370648.55192	123549.51731	33.251	0.0001
Error	35	130048.42244	3715.66921		
C Total	38	500696.97436			

Root MSE	60.95629	R-square	0.7403
Dep Mean	109.35897	Adj R-sq	0.7180
C.V.	55.73963		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-16.111402	18.62261378	-0.865	0.3928
FP	1	0.178449	0.01902015	9.382	0.0001
LANG	1	13.296245	50.35968946	0.264	0.7933
FPLANG	1	-0.110602	0.05875193	-1.883	0.0681

Model: MODEL E
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	357901.50191	178950.75095	45.115	0.0001
Error	36	142795.47245	3966.54090		
C Total	38	500696.97436			

Root MSE	62.98048	R-square	0.7148
Dep Mean	109.35897	Adj R-sq	0.6990
C.V.	57.59059		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	27.297124	85.79029188	0.318	0.7522
UFP	1	0.181938	0.01916323	9.494	0.0001
VAF	1	-58.548003	85.14789104	-0.688	0.4961

Model: MODEL F
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	373735.02344	124578.34115	34.343	0.0001
Error	35	126961.95092	3627.48431		
C Total	38	500696.97436			

Root MSE	60.22860	R-square	0.7464
Dep Mean	109.35897	Adj R-sq	0.7247
C.V.	55.07422		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-239.775295	151.89513159	-1.579	0.1234
UFP	1	0.612086	0.20670226	2.961	0.0055
VAF	1	209.971803	152.14896761	1.380	0.1763
UV	1	-0.428096	0.20490626	-2.089	0.0440

Model: MODEL G
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	378821.55152	126273.85051	36.263	0.0001
Error	35	121875.42284	3482.15494		
C Total	38	500696.97436			

Root MSE	59.00979	R-square	0.7566
Dep Mean	109.35897	Adj R-sq	0.7357
C.V.	53.95971		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-20.371481	82.70074981	-0.246	0.8069
UFP	1	0.177000	0.01806773	9.796	0.0001
VAF	1	5.122305	83.90210664	0.061	0.9517
LANG	1	-60.489773	24.67883454	-2.451	0.0194

Model: MODEL H
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	387817.83247	129272.61082	40.083	0.0001
Error	35	112879.14189	3225.11834		
C Total	38	500696.97436			

Root MSE	56.79013	R-square	0.7746
Dep Mean	109.35897	Adj R-sq	0.7552
C.V.	51.93001		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-23.661420	79.14668651	-0.299	0.7667
UFP	1	0.183943	0.01729221	10.637	0.0001
VAF	1	3.548406	79.43965933	0.045	0.9646
UL	1	-0.090414	0.02968622	-3.046	0.0044

Variable	DF	Tolerance	Variance Inflation
INTERCEP	1	.	0.00000000
UFP	1	0.98771655	1.01243621
VAF	1	0.92399424	1.08225783
UL	1	0.93032886	1.07488872

Collinearity Diagnostics(intercept adjusted)

Number	Eigenvalue	Condition Number	Var Prop UFP	Var Prop VAF	Var Prop UL
1	1.30746	1.00000	0.0988	0.3191	0.2972
2	0.95735	1.16864	0.8821	0.0279	0.1128
3	0.73519	1.33356	0.0190	0.6530	0.5900

Table 24

ANOVA Tables for Commercial Database, All Commercial Data Included, VAF & KSLOC Transformed

Model: MODEL A
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	25.70152	25.70152	58.278	0.0001
Error	37	16.31749	0.44101		
C Total	38	42.01901			

Root MSE	0.66409	R-square	0.6117
Dep Mean	4.19971	Adj R-sq	0.6012
C.V.	15.81272		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.028720	0.18664621	16.227	0.0001
FP	1	0.001496	0.00019595	7.634	0.0001

Model: MODEL B
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	26.24251	26.24251	61.546	0.0001
Error	37	15.77650	0.42639		
C Total	38	42.01901			

Root MSE	0.65299	R-square	0.6245
Dep Mean	4.19971	Adj R-sq	0.6144
C.V.	15.54838		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	2.999831	0.18527209	16.191	0.0001
UFP	1	0.001550	0.00019761	7.845	0.0001

Model: MODEL C
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	29.28581	14.64290	41.399	0.0001
Error	36	12.73321	0.35370		
C Total	38	42.01901			

Root MSE	0.59473	R-square	0.6970
Dep Mean	4.19971	Adj R-sq	0.6801
C.V.	14.16114		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.197430	0.17535246	18.234	0.0001
FP	1	0.001477	0.00017558	8.413	0.0001
LANG	1	-0.751191	0.23597538	-3.183	0.0030

Model: MODEL D
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	29.56998	9.85666	27.712	0.0001
Error	35	12.44903	0.35569		
C Total	38	42.01901			

Root MSE	0.59639	R-square	0.7037
Dep Mean	4.19971	Adj R-sq	0.6783
C.V.	14.20085		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.240080	0.18220314	17.783	0.0001
FP	1	0.001423	0.00018609	7.649	0.0001
LANG	1	-1.137485	0.49271782	-2.309	0.0270
FPLANG	1	0.000514	0.00057483	0.894	0.3775

Model: MODEL E
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	26.24829	13.12415	29.959	0.0001
Error	36	15.77072	0.43808		
C Total	38	42.01901			

Root MSE	0.66187	R-square	0.6247
Dep Mean	4.19971	Adj R-sq	0.6038
C.V.	15.75996		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.101147	0.90158504	3.440	0.0015
UFP	1	0.001553	0.00020139	7.710	0.0001
VAF	1	-0.102812	0.89483394	-0.115	0.9092

Model: MODEL F
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	26.26368	13.13184	30.005	0.0001
Error	36	15.75534	0.43765		
C Total	38	42.01901			

Root MSE	0.66155	R-square	0.6250
Dep Mean	4.19971	Adj R-sq	0.6042
C.V.	15.75227		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.098582	0.48667570	6.367	0.0001
UFP	1	0.001554	0.00020100	7.732	0.0001
VAFSQD	1	-0.099679	0.45324342	-0.220	0.8272

Model: MODEL G
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	26.24254	13.12127	29.941	0.0001
Error	36	15.77647	0.43824		
C Total	38	42.01901			

Root MSE	0.66199	R-square	0.6245
Dep Mean	4.19971	Adj R-sq	0.6037
C.V.	15.76284		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	2.999653	0.18910252	15.863	0.0001
UFP	1	0.001550	0.00020177	7.684	0.0001
LNVAF	1	-0.007033	0.86827526	-0.008	0.9936

Model: MODEL H
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	26.35242	8.78414	19.624	0.0001
Error	35	15.66659	0.44762		
C Total	38	42.01901			

Root MSE	0.66904	R-square	0.6272
Dep Mean	4.19971	Adj R-sq	0.5952
C.V.	15.93067		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.426312	0.88543739	3.870	0.0005
UFP	1	0.001041	0.00116931	0.891	0.3792
VAFSQD	1	-0.427803	0.86784818	-0.493	0.6251
UVSQD	1	0.000504	0.00113255	0.445	0.6589

Model: MODEL I
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	29.25009	9.75003	26.725	0.0001
Error	35	12.76893	0.36483		
C Total	38	42.01901			

Root MSE	0.60401	R-square	0.6961
Dep Mean	4.19971	Adj R-sq	0.6701
C.V.	14.38215		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	2.883376	0.45066645	6.398	0.0001
UFP	1	0.001497	0.00018460	8.109	0.0001
VAFSQD	1	0.300010	0.43676439	0.687	0.4967
LANG	1	-0.725319	0.25351170	-2.861	0.0071

Model: MODEL J
Dependent Variable: LNKSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	30.00509	10.00170	29.138	0.0001
Error	35	12.01393	0.34326		
C Total	38	42.01901			

Root MSE	0.58588	R-square	0.7141
Dep Mean	4.19971	Adj R-sq	0.6896
C.V.	13.95048		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	3.251622	0.17884489	18.181	0.0001
FP	1	0.001417	0.00018278	7.754	0.0001
VAFLANG	1	-1.122414	0.42801323	-2.622	0.0128
ULVSQD	1	0.000516	0.00048166	1.072	0.2910

Variable	DF	Tolerance	Variance Inflation
INTERCEP	1	.	0.00000000
FP	1	0.89451497	1.11792428
VAFLANG	1	0.25223958	3.96448494
ULVSQD	1	0.24688410	4.05048355

Collinearity Diagnostics(intercept adjusted)

Number	Eigenvalue	Condition Number	Var Prop FP	Var Prop VAFLANG	Var Prop ULVSQD
1	1.85974	1.00000	0.0049	0.0661	0.0667
2	1.00875	1.35780	0.8601	0.0073	0.0002
3	0.13151	3.76048	0.1350	0.9265	0.9331

Table 25

ANOVA Tables for Military Database, All Data Included. for Function Point to SLOC Conversion Discussion

Model:A
KSLOC to FP, Lang
Dependent Variable:KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	16443384.48	8221692.2398	177.072	0.0001
Error	52	2414431.385	46431.372788		
C Total	54	18857815.865			

Root MSE	215.47940	R-square	0.8720
Dep Mean	261.83327	Adj R-sq	0.8670
C.V.	82.29642		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	64.361749	43.28867531	1.487	0.1431
FP	1	0.013804	0.00073402	18.806	0.0001
LANG	1	149.624751	58.48957852	2.558	0.0135

Model: B
KSLOC to FP, Lang, FPLANG
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	17077850.18	5692616.7265	163.106	0.0001
Error	51	1779965.685	34901.287941		
C Total	54	18857815.865			

Root MSE	186.81886	R-square	0.9056
Dep Mean	261.83327	Adj R-sq	0.9001
C.V.	71.35031		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	69.496854	37.55024408	1.851	0.0700
FP	1	0.013403	0.00064332	20.833	0.0001
LANG	1	55.987004	55.26139900	1.013	0.3158
FPLANG	1	0.018734	0.00439381	4.264	0.0001

Model: C

KSLOC TO FP (COBOL ONLY PROGRAMS)

Dependent Variable: SLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	1.5148239E13	1.5148239E13	625.760	0.0001
Error	24	580985629439	24207734560		
C Total	25	1.5729224E13			

Root MSE	155588.34969	R-square	0.9631
Dep Mean	240868.07692	Adj R-sq	0.9615
C.V.	64.59484		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	69497	31272.968810	2.222	0.0359
FP	1	13.402644	0.53577998	25.015	0.0001

Model: D

KSLOC TO FP (COBOL ONLY PROGRAMS & NO INTERCEPT)

Dependent Variable: SLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	1.6537143E13	1.6537143E13	590.161	0.0001
Error	25	700534702688	28021388108		
U Total	26	1.7237677E13			

Root MSE	167395.90230	R-square	0.9594
Dep Mean	240868.07692	Adj R-sq	0.9577
C.V.	69.49692		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
FP	1	13.663468	0.56243911	24.293	0.0001

Table 26

ANOVA Tables for Commercial Database, All Data Included, for Function Point to SLOC Conversion Discussion

Model: MODEL E
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	357480.62254	178740.31127	44.930	0.0001
Error	36	143216.35182	3978.23200		
C Total	38	500696.97436			

Root MSE	63.07323	R-square	0.7140
Dep Mean	109.35897	Adj R-sq	0.6981
C.V.	57.67540		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-6.930423	18.59684424	-0.373	0.7116
FP	1	0.166857	0.01862084	8.961	0.0001
LANG	1	-69.857710	25.02615257	-2.791	0.0083

Model: MODEL F
Dependent Variable: KSLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	370648.55192	123549.51731	33.251	0.0001
Error	35	130048.42244	3715.66921		
C Total	38	500696.97436			

Root MSE	60.95629	R-square	0.7403
Dep Mean	109.35897	Adj R-sq	0.7180
C.V.	55.73963		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-16.111402	18.62261378	-0.865	0.3928
FP	1	0.178449	0.01902015	9.382	0.0001
LANG	1	13.296245	50.35968946	0.264	0.7933
FPLANG	1	-0.110602	0.05875193	-1.883	0.0681

Model: G
KSLOC to FP (COBOL Only Programs)
Dependent Variable: SLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	327066637326	327066637326	73.609	0.0001
Error	29	128854782029	4443268345.8		
C Total	30	455921419355			

Root MSE	66657.84534	R-square	0.7174
Dep Mean	125225.80645	Adj R-sq	0.7076
C.V.	53.23012		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-16111	20364.482850	-0.791	0.4353
FP	1	178.448804	20.79920757	8.580	0.0001

Model: H
KSLOC TO FP (COBOL ONLY PROGRAMS & NO INTERCEPT)
Dependent Variable: SLOC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	810412080466	810412080466	184.694	0.0001
Error	30	131635919534	4387863984.5		
U Total	31	942048000000			

Root MSE	66240.95398	R-square	0.8603
Dep Mean	125225.80645	Adj R-sq	0.8556
C.V.	52.89721		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
FP	1	165.137425	12.15119904	13.590	0.0001

Bibliography

1. Albanese, Frank, Jr. *The Application of Regression-Based and Function Point Software Sizing Techniques to Air Force Programs.* MS Thesis, AFIT/GCA/LSY/88S-1. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1988 (AD-A201538).

2. Albrecht, Alan J. and John E. Gaffney, Jr. "Software Function, Source Lines of Code, and Development Effort Prediction: A Software Science Validation," *IEEE Transactions on Software Engineering, Vol, SE-9, 6*: 639-648 (November 1983).

3. Barber, Brent L. *Investigative Search of Quality Historical Software Support Cost Data and Software Support Cost-Related Data.* MS Thesis, AFIT/GSS/LSY/91D-1. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1991 (AD-A246659).

4. Beatty, Richard W. and Craig E. Schneier. *Personnel Administration: An Experiment/Skill-Building Approach.* Reading MA: Addison-Wesley Publishing Company, 1981.

5. Behrens, Charles A. "Measuring the Productivity of Computer System Development Activities with Function Points," *IEEE Transaction on Software Engineering, SE-9, 6*: 649-652 (November 1983).

6. Belsley, David A. and all. *Regression Diagnostics.* New York NY: John Wiley & Sons, 1980.

7. Boehm, Barry W. *Software Engineering Economics.* Englewood Cliffs NJ: Prentice Hall Inc., 1981.

8. Boehm, Barry. "Software Engineering Economics," *IEEE Transactions on Software Engineering, 10*: 4-21 (Jan 1988).

9. Boehm, Barry and Philip N. Papaccio. "Understanding and Controlling Software Costs," *IEEE Transactions on Software Engineering, 14*: 1462-1477 (Oct 1988).

10. Brown, Darlene. "Productivity Measurement Using Function Points," *Software Engineering*: 23-32 (July/August 1990).

11. Conte, S. D. and others. *Software Engineering Metrics and Models*. Reading MA: Benjamin/Cummings Publishing Company, Inc., 1986.

12. Cover, Donna K. "Issues Affecting the Reliability of Software-Cost Estimates (Trying to Make Chicken Salad Out of Chicken Feathers)," *Proceedings of the Annual Reliability and Maintainability Symposium*. 195-201. New York NY: IEEE Press, 1988.

13. Cuelenaere, A.M.E. and others. "Calibrating a Software Cost Estimation Model: Why & How," *Information and Software Technology, 29*: 558-567 (10 Dec 1987).

14. Dorr, Brenda. Afterword to *Function Point Analysis*, by J. Brian Dreger. Englewood Cliffs NJ: Prentice Hall, 1989.

15. Dreger, J. Brian, *Function Point Analysis*. Englewood Cliffs NJ: Prentice Hall, 1989.

16. Emory, C. William and Donald R. Cooper. *Business Research Methods*. Boston MA: Irwin, 1991.

17. Ferens, Daniel V. and Frank Albanese, Jr. Class Handout from IMGT 676, "Software Size Estimation: Deja Vu?" originally published in the *Journal of Parametrics*, (June 1990). School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, February, 1991.

18. Ferens, Daniel V. Class Handout from IMGT 676, *Software Cost Estimation*. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, May, 1992.

19. Ferens, Daniel V. Class Handout from AMGT 553, *Software Size Estimation Techniques*. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, February, 1991.

20. Ferens, Daniel V. Class Handout from SMGT 650, *Management Information Systems.* School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, February, 1992.

21. Ferens, Daniel V. "Computer Software Size Estimation," *Proceedings of the 1988 National Aerospace and Electronics Conference*, 1-6. Dayton OH: 1988.

22. Freund, Rudolf J. and Ramon C. Littell. *SAS for Linear Models.* Cary NC: SAS Institute Inc., 1981.

23. Freund, Rudolf J. and Ramon C. Littell. *SAS for Linear Models.* Cary NC: SAS Institute Inc., 1986.

24. Friedman, Jack P. and others. *Dictionary of Business Terms.* New York: Barron's Eductional Series, Inc., 1987.

25. "Function Point Metrics for Software." Briefing to Air Force Standard Systems Center, Gunter AFB, AL. Tecelote Research Inc., Montgomery AL, June 1990.

26. Gaffney, John E., Jr. and Richard Werling. "Estimating Software Size From Counts of Program Externals, A Generalization of Function Points," *Abstract from the 13th Annual International Conference of the International Society of Parametric Analysts.* 1-5. Herndon VA: Software Productivity Consortium, 1991.

27. Garmus, David. *IFPUG Function Point Counting Practices Manual, Release 3.3.* Westerville OH: International Function Point User Group, 1990.

28. Genuchten, Michiel V. and Hans Koolen. "On the Use of Software Cost Models," *Information & Management, 21*: 37-44 (1991).

29. Grupe, Fritz H. and Dorothy F. Clevenger. "Using Function Point Analysis as a Software Development Tool," *Journal of Systems Management, 42, 12:* 23-26 (December 1991).

30. Gurner, Robert B. *A Comparative Study of the Reliability of Function Point Analysis in Software Development Effort Estimation Models.* MS Thesis, AFIT/GCA/LSY/91S-2. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1991 (AD-A244179).

31. Humphrey, Watts S. *Managing the Software Process.* Reading MA: Addison-Wesley Publishing Company, 1990.

32. IIT Research Institute. *A Descriptive Evaluation of Software Sizing Models.* Report Prepared for the Air Force Cost Center. Rome NY: IIT Research Institute, September 1987.

33. Jones, Capers. "A New Look at Languages," *Computerworld, Vol. 22, No. 45*: 97-103 (November 7, 1988).

34. Jones, Capers. *Applied Software Measurement: Assuring Productivity and Quality.* New York NY: McGraw-Hill, 1991.

35. Jones, Capers. *Applied Software Measurement: The Software Industry Starts to Mature.* Burlington MA: Software Productivity Research, Inc., 1991.

36. Jones, Capers. *International Software Productivity Levels, Version 2.0.* Burlington MA: Software Productivity Research, Inc., 1991.

37. Jones, Capers. "Measuring Software Productivity," *CASE Trends*: 17-18 (January/February 1990).

38. Jones, Capers, President. Personal Correspondence. Software Productivity Research, Inc., Burlington MA, 2 March 1992.

39. Jones, Dub. Personal interview. Standard Systems Center, Gunter AFB AL, 23 March 1992.

40. Jones, Dub. Position Paper on Function Point (FP) Usage. Standard Systems Center/XPG, Gunter AFB AL, 28 July 1990.

41. Jones. Dub. Talking Paper for Function Point Analysis Program. Standard Systems Center/XPG. Gunter AFB AL. 18 Apr 1991.

42. Jones. Dub. Telephone Interview. Technology Transition Section of the Standard Systems Center. Gunter AFB AL. 6 Feb 1992.

43. Jones. Dub. Telephone Interview. Technology Transition Section of the Standard Systems Center. Gunter AFB AL. 27 July 1992.

44. Kemerer. Chris F. "An Empirical Validation of Software Cost Estimation Models." *Communications of the ACM*. 30: 416-429 (May 1987).

45. Keyes. Jessica. "Gather a Baseline to Assess Case Impact." *Software Magazine*. 30-43 (August 1990).

46. Low. Graham C. and D. Ross Jeffrey. "Function Points in the Estimation and Evaluation of the Software Process." *IEEE Transactions on Software Engineering, 16, 1*: 64-71 (January 1990).

47. Marciniak. John J. and Donald J. Reifer. *Software Acquisition Management*. New York NY: John Wiley & Sons. Inc. 1990.

48. McClure. Capt Brant P.. Software Process Database System (SPDS) Program Manager. Personal Interview. Standard Systems Center. Gunter AFB AL. 24 March 1992.

49. Mills. Arthur D. Telephone Interview. Robbins-Gioia Inc. supporting the Cost Analysis Office for the Logistics Management Systems Center. LMSC/SZF. Wright Patterson AFB OH. 24 June 1992.

50. Murphy. Richard. Class Lecture in QMGT 671. Defense Cost Modeling. School of Systems and Logistics. Air Force Institute of Technology (AU). Wright-Patterson AFB OH. 1991.

51. Murphy. Richard. Class Lecture in QMGT 672. Model Diagnostics. School of Systems and Logistics. Air Force Institute of Technology (AU). Wright-Patterson AFB OH. 1992.

52. Neter, John, William Wasserman, and Michael H. Kutner. *Applied Linear Regression Models (Second Edition).* Homewood IL: Richard D. Irwin, Inc., 1989.

53. Neter, John, William Wasserman, and Michael H. Kutner. *Applied Linear Statistical Models (Third Edition).* Homewood IL: Richard D. Irwin, Inc., 1990.

54. Newbold, Paul. *Statistics For Business and Economics* (Third Edition). Englewood Cliffs NJ: Prentice Hall, 1991.

55. Port, Otis and others. "The Software Trap: Automate-or Else," *Business Week*: 142-154 (9 May 1988).

56. "Predicting the Size of Real-Time Systems." Presentation at the Software Cost and Quality Management Conference. Reifer Consultants, Inc., Torrance CA, 30 October 1986.

57. Productivity Management Group, Inc. *Function Point Analysis.* East Amherst NY, 1990.

58. Ourada, Gerald L. *Software Cost Estimating Models: A Calibration, Validation, and Comparison.* MS Thesis, AFIT/GSS/LSY/91D-11. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1991 (AD-A246677).

59. Redding, Phillip L. *A Model for Estimating Aircraft Recoverable Spares Annual Costs.* MS Thesis, AFIT/GCA/LSQ/91S-10. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, September 1991 (AD-A243920).

60. Reese, Richard M. and Jim Tamulevicz. "A Survey of Software Sizing Methodologies and Tools," *Journal of Parametrics, Vol. VII, No. 2:* 35-55 (June 1987).

61. Reifer, Donald J. "Asset-R: A Function Point Sizing Tool for Scientific and Real-Time Systems," *Journal of Systems Software*: 159-171 (November 1990).

62. SAS Institute Inc. *SAS Introductory Guide*, Cary NC, February 1985.

63. SAS Institute Inc. *SAS/STAT User's Guide*. Vol. 1-2. Version 6. Cary NC. February 1990.

64. Schlender. Brenton R. "How to Break the Software Logjam." *Fortune*. 120: 100-101+ (25 Sep 1989).

65. "The SPR Feature Point Method for Realtime and Systems Software." Copy of Briefing sent to Professor Dan Ferens at the Air Force Institute of Technology. Wright-Patterson AFB OH. Software Productivity Research Inc., Cambridge MA. 14 January 1988.

66. Symons. Charles R. "Function Point Analysis: Difficulties and Improvements." *IEEE Transactions on Software Engineering, Vol. 14, No. 1*: 2-10 (January 1988).

67. Symons. Charles R. *Software Sizing and Estimating, Mk II FPA*. New York NY: John Wiley & Sons. Inc. 1991.

68. White. Leonard. Personal Correspondence entitled "The Line of Code (LOC) Measurement Problems Corrected by Function Point Analysis are Many." Productivity Management Group. Inc.. East Amherst NY. 12 July 1990.

69. Woodall. Jack L.. Software Process Database System (SPDS) creator. Personal interview. Science Applications International Corporation. Gunter AFB AL. 24 March 1992.

Vita

Captain Garland S. Henderson was born on 29 December 1962 in Houston, Texas. He graduated from Athens Academy in Athens, Georgia in 1981. In May 1985, he graduated from the United States Air Force Academy with a Bachelor of Science in Human Factors Engineering. Subsequently, he was stationed at Hanscom AFB, Massachusetts in 1986. While there, he served as a Cost Management Systems Analyst for the Electronic Systems Division's Comptroller. In 1987, he served as the Electronic Systems Division Commander's Program Control Room Manager, called the "WAR" Room. In 1988, he attended Squadron Officer's School. Afterward, he served as Human Factors Test Engineer for the Joint STARS System Program Office (SPO). In 1990, he became the Joint STARS Operations and Control Subsystem Test Manager. He served in this capacity until May 1991 when he entered the Air Force Institute of Technology's Graduate Cost Analysis Master of Science Program.

Permanent Address: 215 Rutherford St.
Athens, GA 30605

REPORT DOCUMENTATION PAGE

Form Approved
OMB No 0704-0188

[illegible]

1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 1992	Master's Thesis

4. TITLE AND SUBTITLE	5. FUNDING NUMBERS
THE APPLICATION OF FUNCTION POINTS TO PREDICT SOURCE LINES OF CODE FOR SOFTWARE DEVELOPMENT	
6. AUTHOR(S) Garland S. Henderson, Capt, USAF	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Institute of Technology, WPAFB OH 45433-6583	8. PERFORMING ORGANIZATION REPORT NUMBER AFIT GCA LSY 92S-4
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) SSC XPEP, Building 888 Maxwell AFB - Gunter Annex, AL 36114	10. SPONSORING MONITORING AGENCY REPORT NUMBER
11. SUPPLEMENTARY NOTES	
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release, distribution unlimited	12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)

This research investigated the results of using function point analysis-based estimates to predict source lines of code (SLOC) for software development projects. The majority of software cost and effort estimating parametric tools are categorized as SLOC-based, meaning SLOC is the primary input. Early in a program, an accurate estimate of SLOC is difficult to project. Function points, another parametric software estimating tool, bases software cost and effort estimates on the functionality of a system. This functionality is described by documents available early in a program. Using a modeling methodology, the research focuses on function point's ability to accurately estimate SLOC in the military and commercial environments. Although a significant relationship exists in both environments, none of the models provided a goodness of fit, predictive capability, and significance level to make them acceptable models, especially noted in the variability of the estimates of SLOC. The need to use models developed in similar environments was made clear. The concept of function point to SLOC conversion tables was assessed and was justified. However, the conversion tables to be used should be based on similar programs developed in similar environments. Universally applicable function point to SLOC conversion tables were not supported by this research.

14. SUBJECT TERMS	15. NUMBER OF PAGES
Statistical Analysis, Software Engineering, Cost Estimates, Cost Models, Models, Function Points, Software Estimation	201
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev 2-89)
Prescribed by ANSI Std Z39-18
298-102

AFIT Control Number AFIT/GSM/LSR/92S-4

AFIT RESEARCH ASSESSMENT

The purpose of this questionnaire is to determine the potential for current and future applications of AFIT thesis research. Please return completed questionnaires to: AFIT/LSC, Wright-Patterson AFB OH 45433-9905.

1. Did this research contribute to a current research project?

a. Yes b. No

2. Do you believe this research topic is significant enough that it would have been researched (or contracted) by your organization or another agency if AFIT had not researched it?

a. Yes b. No

3. The benefits of AFIT research can often be expressed by the equivalent value that your agency received by virtue of AFIT performing the research. Please estimate what this research would have cost in terms of manpower and/or dollars if it had been accomplished under contract or if it had been done in-house.

Man Years ______________ $ ______________

4. Often it is not possible to attach equivalent dollar values to research, although the results of the research may, in fact, be important. Whether or not you were able to establish an equivalent value for this research (3, above) what is your estimate of its significance?

a. Highly Significant b. Significant c. Slightly Significant d. Of No Significance

5. Comments

______________________ ______________________

Name and Grade Organization

______________________ ______________________

Position or Title Address

(Fold down on outside — seal with tape)

DEPARTMENT OF THE AIR FORCE
AFIT/ LSC
WRIGHT-PATTERSON AFB OH 45433-6583

OFFICIAL BUSINESS

NO POSTAGE NECESSARY IF MAILED IN THE UNITED STATES

BUSINESS REPLY MAIL

FIRST CLASS MAIL PERMIT NO 1006 DAYTON OH

POSTAGE WILL BE PAID BY THE ADDRESSEE

WRIGHT-PATTERSON AIR FORCE BASE

AFIT/ LSC
WRIGHT-PATTERSON AIR FORCE BASE
DAYTON OH 45433-9905

FOLD IN